

What sustains behavioral changes?

A dynamical systems approach to improving theories of change in physical
exercise

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Richard L. Lenne

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Alexander J. Rothman & Traci Mann

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Dedication

For mom who got me to fall in love with curiosity, dad who gave me perspective and courage, and Eline and Nico who keep me tethered to this earth.

Abstract

Health behaviors, such as physical exercise, are associated with chronic diseases that top the list of all-cause mortality. Yet, the most healthful lifestyle changes people can (and often want to) make, also tend to be the most challenging to sustain. This dissertation explores how modeling behavior as a dynamical system could improve understanding of psychological processes that sustain behavioral changes. I focus on two classes of processes—motivational and habitual—that may be most pertinent to sustaining changes in physical exercise. A model based on prior theorizing is constructed and simulated (Study 1), and observational data are analyzed (Study 2). Intensive longitudinal data are collected from healthy US-based Fitbit users who recently initiated an increase in exercise. Participants are prospectively observed for two months during which measures of motivation and habit are assessed three days per week, and exercise-as-usual is passively tracked via Fitbit. I find that within-person increases in the automaticity with which exercise is performed in a given week is associated with increases in time spent exercising. Furthermore, differences in the trajectory of automaticity and satisfaction with exercise over time may differentiate those who successfully maintain increases in exercise and those who do not. Results are placed in the context of contemporary theories of behavior change maintenance and suggestions for improvement are forwarded.

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1 Introduction

Making and sustaining changes to lifestyle behaviors—exercising, sleeping, eating healthfully, or building relationships—is critical to human health and flourishing. For example, regular physical activity is associated with reduced rates of the chronic diseases that top the list of all-cause mortality (Nocon et al., 2008). Yet, the most healthful lifestyle changes people can (and often want to) make, also tend to be the most challenging to sustain. For example, most New Year’s resolutions involve changing patterns of exercise, diet, sleep, or social interaction, yet most changes are abandoned within a month (ComRes, 2015). Sustaining levels of physical activity that meet national recommendations¹ is particularly challenging, requiring substantial investments of time and effort, in addition to social, environmental, and financial support (USDHHS, 2018).

The concept of entropy serves as an apt metaphor for why certain behavioral changes are so challenging to sustain.² Many have considered how entropy in physical systems may similarly be applied to human behavioral patterns (e.g., DeYoung, 2014; Guastello, 2001; Pinker, 2018; Tooby, Cosmides, & Barret, 2003; van Gelder, 1998; Weiner, 1961). Human behavioral patterns (e.g., one’s pattern of physical exercise) can be thought of as a complex system, the function of which depends upon many constituent parts (i.e., motivation, environment, availability, energy-level, etcetera) interacting with one another over time. Akin to physical systems, such as a hot air balloon, human

¹ For healthy adults the US national guidelines are 150-300 minutes per week of moderate-intensity aerobic physical activity, 75-150 minutes per week of vigorous-intensity, or the equivalent combination (USDHHS, 2018).

² Some argue that the concept of entropy in human behavior is not merely a metaphor, but a fundamental law of psychology (see Tooby Cosmides, & Barret, 2003).

behavioral systems require that the many processes work in concert to maintain functioning: they require order or equilibrium. However, orderly systems are prone to decay over time because, probabilistically, there are simply more ways for the function of the system to deteriorate than there are ways for it to sustain itself. For example, the number of factors that could undermine function of a hot air balloon—a thunderstorm, a structural tear, limited gas, etcetera—far outweighs the confluence of factors maintaining its function. This imbalance only increases over time. Furthermore, introduction of a change or a random perturbation (e.g., a structural tear) to a complex system at equilibrium increases entropy or disorderliness, unless energy is spent to achieve a new equilibrium (Pinker, 2018; Tooby et al., 2003).³ Just as energy is required to stave off the entropy of physical systems, so too may it be required to sustain human behavioral systems. Energy critical to sustaining behavioral systems can, for example, take the form of sustenance, time, knowledge, motivation, social and financial support, etcetera (Pinker, 2018). Thus, there is generally a natural decay of complex systems, and changes to the system tend to disrupt order. Persistent use of energy is required to stave off the entropy of complex systems and to maintain order. Similar to physical systems, any attempt to change patterns in the behavioral system will require energy to combat a natural decay.

Thinking of behavior change in these terms—as a complex system that is prone to decay over time—is useful because it may help to address limitations in the traditional approach to health-behavior research. Traditional theorizing and methodology in this

³ These statements are based on the second law of thermodynamics, which states that physical systems tend to approach more probable states, and dissolve order (or organization) to reach maximal disorder (Feynman, Leighton, & Sands, 1963). Furthermore, highly ordered or complex systems tend to entropy faster (Pinker, 2018; Tooby et al., 2003).

domain tends to be static—in other words, theoretical explanations/predictions and empiricism predominantly focus on a limited period of time in which psychological and environmental variables *unidirectionally* affect behavioral changes (Heckler et al., 2016; Spector & Pindek, 2016). There are expectations (cf. Hall & Fong, 2007; Millar, 2017; Prochaska, DiClemente, & Norcross, 1992; Rothman, 2000; Wood & Runger, 2016), but the fact remains, and recent commentaries concur (Hekler et al., 2016; Michie et al., 2018; Scholz, *in press*; Spruijt-Metz et al., 2015), that there is a dearth of time-intensive and dynamic theorizing in health-behavior research. The focus on relatively static theorizing may, in part, explain why health-behavior interventions are effective at initiating change, but often fail to instantiate lasting changes necessary to prevent disease and promote health (Webb & Sheeran, 2006). In essence, the focus tends to be too narrow, unidirectional, and honed in on single instances of change to inform accurate predictions regarding long-term persistence of changes. In an article on future directions of the field, experts on maintenance of health-behavior change echoed the need for new, process-oriented, longitudinal methods and theorizing (Wing, 2000a, p. 84):

“Maintenance should be conceptualized as a process rather than merely as the last step in the behavior change process. Researchers should focus on understanding how those who are successful at long-term maintenance complete this process and on developing new approaches that can be used to help those who are not successful. Further attention to the following topics was encouraged: observational studies of the natural history of successful long-term behavior change, development of new technologies for measuring health behaviors, better theoretical

understanding of the differences between initial behavior change and maintenance.”

I will argue that thinking of human behavior as a system by adopting techniques common to disciplines such as control systems engineering, ecology, and economics may help achieve goals set forth by Wing and colleagues (2000a)—it may help focus theorizing on *dynamics* (how a system of interrelated variables evolves over time), while also increasing precision and falsifiability of theories.

The objective of the current research is to explore how a complex systems perspective—specifically a dynamical systems approach (Hekler et al., 2016, 2018; Riley et al., 2016)—can improve psychological theory of processes that sustain changes in health-behavior. Drawing on the extant literature, I focus on two classes of factors—motivational and habitual—that may be most pertinent to sustaining health behavior changes. I then further focus on how these factors apply to a domain in which sustaining behavioral changes is particularly challenging—physical exercise. Finally, using a dynamical systems approach, I develop a model to describe how attempts to increase physical exercise may be sustained over time.

2 Theories of Health Behavior Change

The focus of early theorizing in health-behavior change was predominantly on cognitive processes that affect change (Rhodes, Fiala, & Conner, 2009). For example, the theory of planned behavior (Ajzen, 1991; Armitage & Conner, 2001) maintains that people’s attitudes (e.g., “I think exercise is good”), subjective norms (e.g., “I think others believe exercise is good”), and perceived behavioral control (PBC; e.g., “I’m confident in my ability to exercise”) predict their intentions (e.g., “I will exercise”), which in turn

predict their behaviors (i.e., exercising). Additionally, most of the early theories of health-behavior change focus on predicting or explaining *initiation* of change—the health belief model (Rosenstock et al., 1988), theory of reasoned action (Ajzen & Fishbein, 1980), and social-cognitive theory (Bandura, 1986)—and say little about conditions related to *sustaining* or *maintaining* behavioral changes (Rothman, 2000). For example, the theory of planned behavior mentions only briefly maintenance of changes, specifically, that repeated performance of a behavior may lead to re-evaluation of the behavior via the same constructs that were predictive of initiation (Ajzen, 1991). Additionally, social-cognitive theory proposes that self-efficacy (i.e., belief in one’s ability to change) influences both initiation and maintenance, and may change with repeated behavior (Bandura, 1986). Both of these theories, and other traditional theories like them, underspecify predictions regarding how behavior change is sustained—perhaps because they were not intended to address the issue, and because methodological and analytical techniques required to test time-intensive predictions were not as robust as they are today (Spruijt-Metz et al., 2015). As a consequence, health interventions based on these classic theories often fail to instantiate *lasting* changes necessary to prevent disease and promote health, despite being moderately effective at *initiating* changes in many health domains (Webb & Sheeran, 2006). Similarly, according to reviews of the psychological literature, physical-activity interventions produce modest initial changes, but often fail to result in long-term changes (Lewis et al., 2002; Rhodes & Pfaeffli, 2010).

More recent theorizing on health-behavior change has increasingly considered the effect of motivational processes (such as affective experience associated with the behavior; for reviews see Rhodes, Fiala, & Conner, 2009; Williams & Evans, 2014,

Ekkekakis et al., 2016) and habitual processes (such as stability of context in which the behavior is performed; for review see Wood & Rünger, 2016), in addition to the traditional cognitive focus. Additionally, a growing number of theories focus specifically on processes related to sustaining health-behavior changes (e.g. Rothman, 2000). Employing liberal search parameters, a recent review of health-behavior research identified one hundred theories and models (many of which are closely related) that at least peripherally address sustained changes (Kwasnicka et al., 2016). As is evident from the review, motivational and habitual predictors of sustained behavior change emerge as primary themes across theories.

Another dimension that characterizes many theories of sustained behavioral changes is the extent to which they define distinct phases of behavior change (e.g., initiation versus maintenance). Some theories make predictions that inherently emphasize sustained behavioral change, but do not directly address distinctions between phases. For example, habit theories (e.g., Wood & Neal, 2007) do not address distinctions because these theories attempt to describe self-sustaining or automatically and regularly cued behavioral patterns. In contrast, other theories are primarily focused on differentiating phases of behavior change (e.g., “stage models”).

In what follows, I highlight two prominent stage models of behavior change common to health-behavior research. I then use them to organize a review of motivational and habitual processes that sustain changes in a particular health behavior—physical exercise.

1.1 Stage Models of Behavior Change

A growing number of theories more directly address processes that sustain behavioral changes. In particular, stage models are often used in public health research. One example is the popular transtheoretical model (Prochaska, DiClemente, & Norcross, 1992; Di Clemente & Prochaska, 1982), which primarily marks stages of change by time, one of which involves “maintenance” (also see Plotnikoff & Higginbotham, 2002; Plotnikoff et al., 2007). Despite wide adoption in public health and physical activity research (Spencer et al., 2006), there are limitations to this approach. First, many of these theories are unclear about how to determine whether someone is in a particular stage. For example, the transtheoretical model makes the nonspecific observation that people in the maintenance phase are working to “prevent relapse and consolidate the gains attained during action,” and says little about the psychological processes that support people in this phase (Prochaska & Velicer, 1997). Additionally, clearly defining the distinction between initiation and maintenance has proven thorny. Many of the stage models suggest specific time periods to mark transitions from initiation to maintenance (e.g., Prochaska, DiClemente, & Norcross, 1992). For instance, in the domain of smoking, most relapses occur within three months of initial cessation, and are often followed by several cycles of cessation and relapse prior to successfully quitting (Ockene et al., 2000). Thus, for many smokers, three months after the initial quit date may mark the transition to a maintenance phase. In other health domains, such as physical exercise, what qualifies as a relapse is not as easily defined (Wing, 2000b), in part because the time cut-off is more varied across contextual and individual factors (Kwasnicka et al., 2016).

Instead of focusing on temporal markers of behavior change stages, Rothman and colleagues focus on psychological markers (Rothman, 2000; Rothman et al., 2004;

Rothman, Hertel, Baldwin, & Bartels, 2008). Their conceptual framework highlights four phases of behavior change—initial response, continued response, maintenance, and habit—each of which can be identified from a unique set of psychological conditions (for summary see Table 1). The proposed conditions can be classified into three classes, which are coherent with those identified in recent reviews of theories of behavior change (Kwasnicka et al., 2016; Rhodes et al., 2009). First, cognitions related to behavioral *beliefs* and *intentions* (e.g., self-efficacy, outcome expectations, and normative beliefs) are proposed to be of primary importance to behavioral initiation (i.e., first reliable performance of the behavior). Second, *motivational* processes (e.g., satisfaction, affective experience, and rewards) are of primary importance to continued response and maintenance phase (i.e., sustained effort to continue newly established behavior). Third, factors related to habitual processes such as *stability of the behavioral context* and *automaticity of the behavior* are of primary importance to the habit phase (i.e., self-perpetuating pattern of behavior).

This framework is useful to the present research for two reasons. First, it highlights distinct psychological constructs that are relevant across phases of behavior change, from initiation to long-term sustained behavior change. Second, it makes more specific predictions about how these variables might evolve over time as a person continues to pursue a change in behavior. In other words, this framework helps organize a set of variables that can be used to specify behavior change as a dynamical system.

There are, however, limitations to this framework that the present research aims to address. First, there is no guidance on how these variables may evolve and interact with each other over time. Different trajectories of these variables over time may have

different consequences for one's ability to maintain changes in physical exercise.

Furthermore, the framework says little about how feedback or iterative processes might play a role. Second, the framework is useful for thinking about many different types of behaviors, which is laudable. However, for complex behaviors (such as physical exercise that requires substantial effort), the proposed constructs guiding the theoretically distinct maintenance and habit phases may be playing a more active role across phases. In what follows I present empirical support that motivational processes can be predictive of physical-exercise behavior across phases of change. Thus, the line between maintenance and habit phases may be blurred. Second, I will describe how a dynamical systems approach is effective at capturing changes across phases; and deepening our theoretical understanding of how psychological variables relevant to sustaining behavioral changes evolve over time.

Table 1. Phases of Behavior Change

| Phase | initial response | continued response | maintenance | habit |
|--------------------------------------------------|------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|-------------------------------------------------------|
| defining feature of phase | Initial effort to change behavior (e.g., enrolling in a program) | Continued effort to establish new behavior | sustained effort to continue newly established behavior | Self-perpetuating pattern of behavior |
| Primary determinants of transition to next phase | Efficacy beliefs (++) | initial reward (+) | Satisfaction with new behavior (++) | Prior behavior (++) |
| | Outcome expectations (+) | Sustained self-efficacy beliefs (+) | Personality/situation (-) | Frequency-in-context (context stability; Wood et al.) |
| | Personality/situation (-) | Sustained outcome expectations (+) | Affective Judgments and Responses | Automaticity (Gardner et al.) |
| | | Demands of the behavior change process (--) | | Both (Verplanken & Orbell; Tappe & Glanz) |
| | | Personality/situation (--) | | |
| Marker of end of phase/beginning of next phase | First reliable performance of the desired behavior | Consistent performance of the desired behavior and complete confidence in one's ability to perform the behavior | Consistent behavior without consideration of the value of the behavior | |

Note: Recreated with permission from Rothman et al., 2004. Grey cells are additions to the original table.

3 Processes that Sustain Changes in Physical Exercise

1.2 *Maintenance Phase: Motivational Processes in Physical Exercise*

There are many theories of motivational factors pertinent to sustaining behavioral changes— affective assessments such as enjoyment or intrinsic rewards derived from the behavior (self-determination theory; Deci & Ryan, 1985), perceived satisfaction with behavioral outcomes (model of behavioral maintenance; Rothman, 2000), and congruency between identity and the behavior (regulatory fit theory, Higgins, 2005; identity-based motivation theory; Oyserman, Smith, & Elmore, 2014). Affect and satisfaction are often used to study long-term sustained changes in physical activity, and thus will be the focus of the following sections. There are several reasons why theories highlight these constructs as particularly important to sustained changes. First, affect tends to be a more proximal, intrinsic, and automatically activated driver of behavior. In essence, it is more stable across time and context, and more deeply embedded in memory than are cognitive constructs, evidence for which is elaborated on below. Second, after initiating a behavioral change, outcomes and experiences resulting from the new behavioral pattern become a person's focus. This shift in perspective, from future-oriented beliefs and expectations that guided initiation of the behavior to satisfaction with outcomes that guides maintenance of behavior, comes naturally. For example, the question people ask themselves during initiation, “Do I think I will benefit from making a change?” naturally shifts after behavior change is initiated to “Having made the change, is it currently benefiting me?”. Each of these reasons for focusing on motivational processes and associated theories will be discussed in what follows.

1.2.1 Affective Experience

Several types of affective assessments are frequently studied in the domain of physical activity (for reviews Rhodes et al., 2009; Williams & Evans, 2014). *Affective judgments* are assessments of the overall pleasure/displeasure, enjoyment, and feeling states associated with enactment of a behavior (Rhodes, Fiala, & Conner, 2009). This definition often includes future affective expectations regarding the behavior (e.g., “physical activity would be enjoyable”), affective judgments of past physical activity performances (e.g., “physical activity was pleasurable”), and affective experiences associated with physical activity (e.g., “physical activity makes me happy”), but excludes assessments of feeling states (e.g., pleasure or pain) *during the act* of physical exercise. These in-the-moment-feeling assessments are often considered to be a distinct construct, termed *affective responses* (Ekkekakis, Hall, & Petruzzello, 2008). *Incidental affect* (e.g., mood fluctuations throughout the day) is a third affective assessment that is frequently studied in the physical activity domain (see Dunton, 2017; Dunton & Atienza, 2009). However, most theories and empirical analyses of long-term sustained physical activity focus on affective *judgments* and *responses*, which will also be the focus of the present research.

Several theories emphasize the particular importance of *affective judgments* to sustained physical activity, primarily for two reasons. First, in the physical-activity domain, *affect*-related outcomes tend to be more proximal than *cognitive*-related outcomes (e.g., enjoyment can be experienced during or soon after exercise, whereas health benefits have a longer latency; Rhodes et al., 2009). Proximal outcomes are more important to day-to-day action than are distal ones (Hall & Fong, 2007) and immediate

feedback is critical to habit formation (Wood & Runger, 2016). Second, in the physical activity domain, *affective* constructs tend to be internal (intrinsic) motivators (e.g., enjoyment of exercise in and of itself; Ryan et al., 1997; Teixeira et al., 2012). Intrinsic motives are critical to positive self-concept and autonomy needs (Deci, Koesterner, & Ryan, 1999), and are more stable across time and context than are extrinsic motives (Vallerand & Ratelle, 2002), which is why they may be particularly relevant to sustaining physical activity long-term. Some of the theories that highlight affective judgments include recent thinking on the theory of planned behavior which distinguishes between affective and instrumental types of outcome expectations—the *affective* type being emotion-laden judgments about the consequences of the behavior, whereas the *instrumental* type assesses cost-benefit judgments of the behavior (Lowe et al., 2002 French et al., 2005; Kraft et al., 2005). The former is theorized to be more important to sustained physical activity. Additionally, self-determination theory (Deci and Ryan, 1985)— frequently used as a framework for interventions promoting physical activity (Hagger & Chatzisarantis, 2007)—highlights the importance of affective judgments for long-term changes. For instance, intrinsic motivation (e.g., exercising because of inherent rewards such as feelings of enjoyment or personal accomplishment) and autonomous motivation (e.g., *wanting to* exercise as opposed to feeling as though one *has to* do it) are both theorized to be particularly relevant to sustained physical activity. This is because intrinsic and autonomous motivations reflect internal instead of external motives (Ryan et al., 1997; Teixeira et al., 2012). Similarly, behavioral choice theory (Vuchinich & Tucker, 1983) implicitly recognizes the role of affect in sustained physical activity using the concept of a “reinforcing value,” a reward that can be intrinsic or extrinsic. Again, the

intrinsic type is theorized to be particularly pertinent to long-term change. In sum, affective judgments of physical activities are proximal and intrinsic drivers of behavior, and several theories view these judgments as especially relevant to sustaining changes long-term.

These theories tend to emphasize that affective judgment is a relatively deliberative (i.e., conscious) process that influences behavioral decisions. For example, people think about and are aware of the enjoyment that they derive from exercising, and use these assessments to determine whether they will continue to persist with the activity over time. In contrast to this perspective, theories that address the role of *affective responses* (i.e., in-the-moment affect) in sustaining physical activity tend to emphasize the non-deliberative or automatic way in which they do so (Ekkekakis et al., 2016). This theoretical perspective often draws on dual-process or dual-system theories (Evans & Stanovich, 2013), such as Strack and Deutsch's (2004) Reflective-Impulsive Model (RIM). Using this approach, Hofmann, Friese, and Wiers (2008) explain how many health-behavior decisions are affected by "associative clusters" stored in long-term memory, which are gradually formed by "temporal or spatial co-activation of external stimuli, affective reactions, and associated behavioral tendencies" (p. 115). For instance, repeated exercise with friends at a particular gym may form an associative cluster that connects the concept of exercise with positive hedonic affect. Once formed, such associative clusters can be reactivated quickly or automatically by external stimuli (e.g., being near the gym) and/or internal conditions (e.g., loneliness) to guide behavioral decisions. Drawing on these theories and the "affect heuristic" (Finucane, Alhakami, Slovic, & Johnson, 2000), some researchers reason that one's history of affective

responses (i.e., one's associate clusters) will be more predictive of long-term sustained physical activity than will the more deliberative construct of affective judgments, because: (1) automatic processes tend to be the default decision-making mode (Ekkekakis et al., 2016), and (2) automatic processes at least partially guide deliberative decisions (Strack & Deutsch, 2004; Hoffman, Friese, & Wiers, 2008).

A growing body of evidence supports both theoretical perspectives. Affective *judgments* associated with exercise and affective *responses* to bouts of exercise are both reliable predictors of the amount of physical activity people choose to do in their daily lives (for reviews: Rhodes, Fiala, & Conner, 2009; Rhodes & Kates, 2015; Williams & Evans, 2014). However, evidence for predictors of *higher levels* of physical activity is not the same as evidence for predictors of *sustained increases* in physical activity. The latter, which is my focus, is about what happens after a change is made, whereas the former could have arisen after a change, but could also describe an individual difference between those who exercise a lot and those who do so only a little. There are no reviews focused specifically on predictors *sustaining a recent increase* in physical exercise. There are, however, empirical examples, many of which are a part of the cited reviews. For instance, Ingledew, Markland, and Medley (1998) interviewed exercisers as they moved through different stages of change. Using the transtheoretical model as their framework, they found that beliefs (such as expectations about improving one's body) were prominent in the precontemplation, contemplation, and initiation stages, whereas affective experiences, especially enjoyment of physical activity, were associated with action and maintenance stages of physical activity.

Taken together, there is clear theoretical and empirical support (waiting in anticipation for a review) for the proposition that affective experiences—whether deliberative judgments or automatic responses—are particularly relevant to sustaining increases in physical activity. I now turn to a second motivator that is also relevant in this domain: satisfaction with experienced outcomes.

1.2.2 Satisfaction with Experience

A second motivational process that is related more specifically to sustaining recent changes in physical activity (as opposed to merely being associated with higher levels of it) comes from Rothman and colleagues (2000; 2004; 2008). They propose that decisions regarding behavior-change maintenance tend to depend on *perceived satisfaction* with *outcomes* or *experiences*. In other words, sustaining a change in one's pattern of behavior involves continuous assessment of the behavior's current value. It involves questions such as, is the new behavioral pattern meeting my expectations? And, is the new behavior still rewarding? This framework proposes that during the maintenance phase, outcome expectancies and self-efficacy (cognitive constructs) likely remain high, but are no longer continuously evaluated. Beliefs about the behavior and expectations regarding potential outcomes affect initiation of change, but after the change has been initiated one's focus shifts to the lived experience of the change and the outcomes that have resulted from it (Baldwin & Sala, 2018). There is growing empirical support for this hypothesis in the health domain, particularly for smoking cessation, weight loss, and physical activity. For example, Baldwin et al. (2006) found that satisfaction with the outcomes of smoking-cessation efforts predicted quit status for those quitters who were struggling to maintain abstinence. In the exercise domain, Fleig and

colleagues (2011) found that satisfaction better predicted maintaining a rehabilitation program than did intentions to do so. Furthermore, a review and meta-analysis found a moderate positive relation between satisfaction with exercise and sustained engagement in it (Rhodes, Fiala, & Conner, 2010). There are, however, examples in which satisfaction with outcomes was not predictive of sustained physical activity (e.g., Phillips et al., 2016). Taken together there is adequate evidence that perceived satisfaction with experiences is a likely predictor of sustained increases in physical exercise.

1.3 Habit Phase: Habitual Processes in Physical Exercise

The final phase of Rothman and colleague's conceptual framework of behavior-change maintenance is *habit* (see Figure 1). The habit concept is foundational to psychology and human behavior (e.g., Barandiaran & Paolo, 2014; James, 1890; Watson, 1913) and is colloquially synonymous with long-term, sustained behavior change (Gardner, 2015). The habit phase of behavior change is predominantly guided by automatic (unconsciousness, non-thinking, or non-evaluative processes) and contextual factors. This stands in contrast to the more deliberative processes and psychological factors implicated in the initiation phase (i.e., beliefs, expectations, and intentions) and the maintenance phase (i.e., motivations related to affective judgments and satisfaction with experience). In the context of psychological theories of behavior change, habits involve two critical components that may predict sustained changes in behavior, and that are the focus of the following sections—*context stability* and *automaticity*. In what follows, I will also suggest that the theoretical distinction between the automatic habit phase and the more deliberative maintenance phase may be blurred for complex behaviors such physical activity. In particular, I address how complete automaticity of

complex behaviors is unlikely, and how differentiating between two sub-actions in complex behaviors—*instigation* and *performance*—may help to better elucidate the circumstances in which habitual processes sustain changes to physical activity and how they may interact with motivational processes.

1.3.1 Context Stability

Habits are formed when a behavior is paired with a particular contextual cue many times, after which the behavior operates automatically whenever the cue is present (Gardner, 2015; Rebar, 2017; Verplanken, 2006; Wood & Neal, 2007; Wood & Rünger, 2016). Because habits are closely linked to the context in which they take place, changing the context may inhibit persistence of the behavioral pattern. For example, a person who exercises on a strict schedule may find it harder to exercise on vacation because she may need to change the time and place of her workout. Thus, contextual cues that are relatively stable and consistent in their support of a behavioral pattern will enable persistence over long periods of time. Context can also extend beyond external cues (such as time and location) to include internal psychological cues such as one's mood or the social situation (Rebar, Gardner, & Verplanken, 2018; Verplanken, 2009; Wood & Neal, 2016; Wood & Rünger, 2016). Habits derived from context stability are associated with increases in a variety of behaviors, including fast-food purchases, television-news viewing, travel-mode choices, and exercise; and are thoroughly reviewed (e.g., Friedrichsmeier, Matthies, & Klöckner, 2013; Ji & Wood, 2007).

1.3.2 Automaticity

Context stability is critical to habit formation in that it enables automatic associations between cues and behavior. In other words, frequent pairing of an action

(e.g., buckling one's seatbelt) with a particular context (e.g., upon sitting in an automobile), increases the automaticity with which the action is executed. After repetition, the action is spontaneously elicited when the context is encountered. Research on habit formation has traditionally involved *simple* behaviors such as lifting latches, pressing keys, or pushing buttons (e.g., Watson, 1913; de Wit & Dickinson, 2009). It is often presumed that the automaticity that forms for *simple* behaviors will similarly take form in more *complex* behaviors, such as dieting or exercising, which tend to be harder to perform (Gardner, 2015). Because *complex* behaviors implicate many sub-actions and can take place in diverse contexts, complete automaticity of the behavior is unlikely (Maddux, 1997). For example, one study found that behaviors such as drinking water throughout the day (minimal number of sub-actions; mildly varied context) or wearing a seat belt when driving (minimal sub-action; consistent context) are more easily made automatic (and start to look like full-blown habits) than are more complex behaviors such as doing sit-ups every day (middling sub-action; varying context; Lally et al., 2010).

Recognizing that complex behaviors may never be fully automatic, some researchers draw a distinction between *habits* and *habitual behavior*. A *habit* is a psychological process that is automatic and spontaneously elicited. In contrast, *habitual behavior* is a highly regular behavior that results from the habit process but can be inhibited by, for example, motivational processes such as external rewards; habitual behavior is never fully automatic (Rebar, Gardner, Rhodes, & Verplanken, 2018; Gardner, 2015; Hagger, 2019). For complex behaviors, it is more likely that only some of the behavior's sub-actions are automatic, and thus these complex behaviors are unlikely to ever be fully formed habits by traditional definitions. That said, some of the sub-

actions involved in complex behaviors *can* become automatic, and the resulting behavior starts to look “habitual” (Gardner, 2015; Rebar et al., 2018). Empirical evidence suggests that habitual behaviors require less attention, self-control, and memory than do non-habitual behaviors, because more (but not all) of their sub-actions operate automatically (Aarts et al., 1997; Orbell & Verplanken, 2010; Verplanken et al., 1997; Wood et al., 2002). For example, a person may automatically (without thinking) prepare a gym bag in the morning and drive to the gym; however, the exercises they choose to engage in at the gym unfold with greater conscious deliberation. Thus, for complex behaviors such as physical exercise, it is important to consider the degree to which sub-actions are engaged in automatically (e.g. without much thinking or awareness) in addition to the stability of the context in which they are engaged (Gardner, 2015; Rebar et al., 2018).

Increases in automaticity are associated with longer-term sustained changes in physical activity. For example, one meta-analysis revealed moderate-to-strong effects between automaticity and subsequent levels of physical activity and sedentary behaviors ($r = .43$ and $r = .47$, respectively; Gardner et al., 2011). A recent review identified 37 studies of automaticity for exercise (or physical activity) and found a medium sized association with activity ($r = 0.32$; Rebar et al., 2016). Similar to reviews of affective experiences, these reviews mix studies on associations with higher levels of exercise and those on associations with sustaining recent increases in exercise. For example, many studies in these reviews are cross-sectional and show that people with higher levels of exercise report greater automaticity than those with lower levels of exercise; in contrast, longitudinal studies show that within-person or between-person changes in automaticity over time are associated with maintaining recent increases in exercise. There are no

reviews focused exclusively on the latter—which is my focus—though there are many empirical examples that I discuss in what follows. However, I must first touch on another important theoretical distinction that arises from thinking of exercise as a complex behavior with many sub-actions.

1.3.3 Sub-actions in complex behaviors: instigation vs. performance

In order to better understand how to sustain changes in complex behaviors such as exercise, Gardner (2015) distinguishes between *instigation* and *performance* of the behavior. *Instigation* involves a set of decisions and/or actions that enable performance of a target behavior (such as packing a gym bag). Say, for example, the target behavior is commuting to work by bicycle. Planning the night before and deciding in the morning whether to bike or take another form of transportation are forms of *instigation*. In contrast, *performance* involves decisions and actions required to execute the target behavior, for example, what it takes to make the journey to work by bike (e.g., pedaling, route selection, pace). The degree of automaticity involved in instigation and performance may vary. For example, deciding to bike (*instigation*) may reflect a deliberative process, but enacting the subsequent pattern of action required to get to work (*performance*) may happen automatically, with little conscious thought. Thus, Gardner (2015) proposes that there are three distinct types of habitual behaviors (Table 2), with the above example falling into Type 3. Gardner’s framework may clarify conceptual differences in how health-behavior researchers define “habit.” For example, some treat habitual exercise as both automatically instigated and performed (Type 1; Aarts et al., 1997), whereas others imply that instigation is automatic, but performance can remain deliberative (Type 2; Verplanken & Melkevik, 2008). Indeed, Philips and Gardner (2015)

have found support for the idea that automaticity of instigation is empirically distinct from automaticity of performance for physical activity.

Table 2. Theoretically distinct types of habitual behaviors

| Behavior | Instigation | Performance |
|-----------------|---------------------|---------------------|
| Habitual Type 1 | <i>Automatic</i> | <i>Automatic</i> |
| Habitual Type 2 | <i>Automatic</i> | <i>Deliberative</i> |
| Habitual Type 3 | <i>Deliberative</i> | <i>Automatic</i> |
| Non-Habitual | <i>Deliberative</i> | <i>Deliberative</i> |

Furthermore, potential differences among the three types of habitual behaviors may have practical implications. For example, if the goal is to encourage more bike commuting, and people usually complete the commute once they have mounted their bike, it may be best to intervene on instigation (make it more automatic) because once initiated, the commute will be completed regardless of how deliberative or automatic the performance (i.e., Type 1 or 2). In an initial test of this idea, Philips and Gardner (2015) found that automaticity of instigation (as opposed to automaticity of performance) was most strongly associated with frequency of exercise over a month-long observation period. Furthermore, changes in automaticity of instigation from baseline to one-month follow-up was the only predictor associated with changes in frequency of exercise. Additionally, interventions aimed at helping people make instigation behavior more automatic may be a particularly effective and efficient way to increase physical activity (e.g., Kaushal et al., 2017). These studies indicate that Type 2 habitual behavior may be most predictive of sustained changes in physical exercise.

The distinction between instigation and performance may be useful in exploring potentially different psychological consequences of engaging in complex behaviors. But it is important to further understand why this distinction may be important in a given

scenario. In particular, motivational processes may differentially interact with instigation and performance behaviors. For instance, instigation behaviors may be less rewarding (deciding, planning, or engaging in other activities that feel ancillary to primary goals can be unpleasant), whereas some aspects of behavioral performance can be rewarding (e.g., feeling accomplished after completing a challenging workout). In fact, there is some evidence that physical activity and exercise in particular offer more opportunities for pleasure than do most other health-related behaviors (e.g., flossing, buckling up, and seeing the doctor; Dishman, 2013). In the next section, I explore how motivational processes may interact with habitual processes in instigation and performance to affect persistence of behavioral changes.

1.4 Integrating Motivational and Habitual Processes to Predict Sustained Physical Activity

The distinctions between *habit* and *habitual*, and *instigation* and *performance* for complex behaviors are useful because they recognize that some behaviors are less likely to be determined solely by automatically activated processes, even in the habit phase. In fact, complex behavior may be more likely to inspire strong motives or to require at least some deliberative (or evaluative) process. This blurs the line between the maintenance and habit phase as conceived by Rothman and colleagues (Table 1). Their framework is useful for thinking about many different types of behaviors; however, for complex behaviors, the proposed constructs guiding the theoretically distinct maintenance and habit phases may be playing a more active role. The different types of habitual behaviors indexed by *instigation* and *performance* (Table 2) may have different psychological consequences that shift over time, differentially affecting long-term engagement in the

behavior. In what follows I highlight several hypotheses that will be tested. These hypotheses are derived from empirical evidence in which motivational processes and habitual processes affect sustained changes in physical activity, but also intermingle across phases of change, particularly in the maintenance phase.

1.4.1 **Hypotheses for processes that sustain physical exercise**

Hypothesis 1: Motivational and habitual processes are positively associated with sustained increases in physical exercise over time (see sections 3.1 and 3.2 for evidence). Specifically, higher levels of both positive affective experiences and satisfaction will help people maintain increases in physical exercise. Additionally, higher levels of automaticity and context stability, for both performance and instigation, will also help people maintain increases in physical exercise.

Hypothesis 2: Motivational processes affect habitual processes, particularly instigation, which in turn affects sustained behavior.

Motivational processes may play an active role across phases of change, particularly in catalyzing (more rapidly increasing) habitual instigation in the maintenance phase. Several theorists support this hypothesis, including proponents of the Associative Cybernetic Model, which proposes that experiencing a behavior as rewarding can accelerate learning of cue-response associations (de Wit & Dickinson, 2009). There is also ample empirical support. For example, Phillip and colleagues (2016) found that *affective judgments* predicted physical activity in both initiation and maintenance phases, although through distinct mediational pathways. Affective judgments affected intentions in the initiation phase and automaticity in the maintenance phase, and, in turn, intentions and automaticity-predicted behavior. Similarly, Radell et al. (2017) found that

automaticity of a variety of behaviors, including running and exercising at the gym, was partially driven by affective judgments, particularly during the maintenance phase. People who found exercising more rewarding formed stronger habits for the behaviors (and formed them faster) than did those who did not find them rewarding. Gardner and Lally (2013) also found that motivational processes determined whether frequent physical activity became habitual. For people who did not find activity intrinsically rewarding, frequent physical activity was less likely to be automatic compared to people who did find it rewarding. Thus, motivational processes (particularly intrinsic rewards) for exercising appear to accelerate automaticity of the behavior across phases of change. People who are intrinsically motivated to be physically active initiate changes, maintain those changes, and form habits of them (Rebar et al., 2018).

Measures of automaticity in these studies were general—not specific to instigation or performance. However, conclusions from these studies may be primarily relevant to automaticity of instigation, because analyses of instigation-specific, performance-specific, and non-specific automaticity indicate that people are mainly thinking of instigation of exercise when answering non-specific questions (Gardner, Philips, & Judah, 2016).

Hypothesis 3: Habitual processes in performance undermine motivational processes, which may result in failure to sustain behavior (**Part A**), yet, habitual processes in performance make it easier to enact the behavior, which may also help sustain it (**Part B**).

There are two competing ideas for how habitual performance and motivational processes sustain increases in physical activity (Sherwood & Jeffery, 2000). First, less

automaticity in performance (or a less stable context) could sustain behavior change by increasing positive motivation (intrinsic rewards) or by reducing negative motivation (boredom). For example, many long-time regular exercisers purposefully vary their exercise routine (reducing automaticity and context stability of performance) in order to maximize enjoyment/challenge or to minimize boredom (Verplanken & Melkevik, 2008). In other words, varying the performance of exercise may prolong motivational rewards derived from the experience (i.e., bolster affective experiences), which may help to maintain increases in physical activity for longer. Second, more automaticity in performance (or more stability) could sustain behavior change by reducing decision-making or increasing ease of action (evidence for which was discussed in section 3.2.2). Some authors have suggested a resolution to this tension, which leads to a fourth hypothesis.

Hypothesis 4: Increasing habitual processes in instigation while maintaining middling levels of habitual processes in performance is most likely to sustain behavioral changes (Type 2 Habitual Behavior from Table 2).

Some researchers have suggested that reducing variety (increasing stability and automaticity) of *instigation* behaviors while maintaining variety (middling levels of stability and automaticity) in behavioral *performance* may prolong maintenance of exercise (Gardner & Lally, 2013; Gardner, 2015). In other words, this scenario may increase frequency of performance (because instigation is automatic) while prolonging intrinsic rewards associated with performance (because it is more deliberative and varied). In fact, there is evidence that slightly increasing variety in exercise performance (which is antithetical to context stability and automaticity that also drives sustained

behavior) increases motivational rewards and helps sustain the behavior (Glaros & Janelle, 2001; Juvancic-Heltzel, Glickman, & Barkley, 2013). The mere *perception* of variety may also increase motivation and maintenance. For example, participants who received a message about the variety of experiences to expect for two upcoming exercise sessions (as opposed to a message noting the similarities between the two exercise sessions) reported more intrinsic rewards after repeating the exercise session (Dimmock, Jackson, Podlong, & Magaraggia, 2013). Similarly, from a learning theory perspective, increasing variety of the context in which exercise takes place helps generalize the behavior to future contexts in which it could take place, increasing the likelihood it is sustained long-term (Bouton, 2000).

1.5 Summary of Hypotheses on Processes that Sustain Changes in Physical Exercise

The extent literature suggests that three motivational processes (affective judgments, affective responses, and satisfaction) and two habitual processes (context stability and automaticity) are critical to sustaining changes in physical exercise. Prior theories have suggested that a maintenance phase (dominated by motivational processes) proceeds and is distinct from a habit phase (dominated by habitual processes). I have presented empirical support that motivational processes and habitual processes are relevant across phases of behavior change, at least for complex behaviors (such as physical exercise), which involve many distinct sub-actions (such as instigation v. performance). Figure 1 depicts a path diagram and summary of hypotheses for how these constructs may intermingle to sustain changes in physical exercise. Solid arrows denote an association between each construct and sustained physical exercise, and green and red

text represents positive and negative associations, respectively. For example, after an initial increase in physical exercise, increases in affective judgments are positively associated with continued maintenance or further increases in physical exercise over time (H1). Mediational hypotheses are also depicted. For example, increases in positive affective judgments are associated with increases in instigation automaticity, which in turn is positively associated with continued maintenance (H2). Additionally, increases in automaticity of performance negatively influence affective judgments, which are, in turn, positively associated with sustained exercise (H3a). Furthermore, some of the depicted hypotheses are not easily represented in a path diagram traditional to health-behavior theorizing (Figure 1). For example, H4 is a prediction regarding middling levels of performance stability/automaticity and high levels of instigation stability/automaticity, which is theorized to result in optimal conditions for sustained physical exercise.

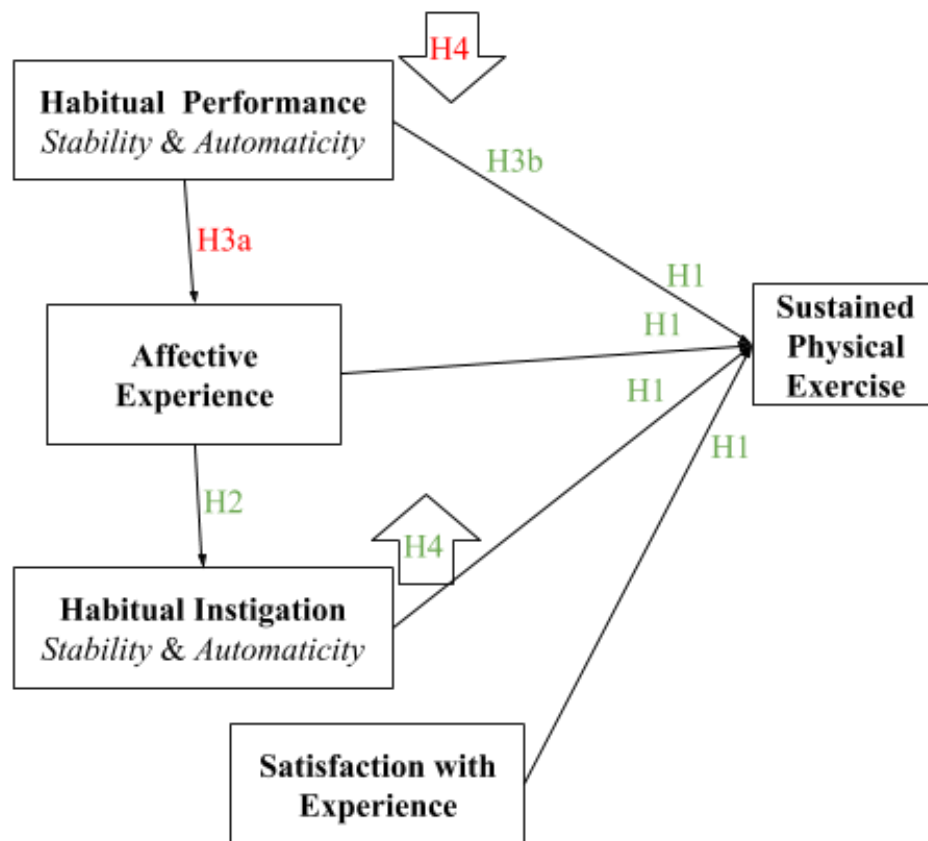


Figure 1. Path diagram of processes that sustain changes in physical exercise during maintenance and habit phases

As is evident from these hypotheses, there are many ideas in the literature regarding relations between and among motivational and habitual processes and sustained physical activity during both maintenance and habit phases. These myriad ideas are challenging to represent in a path diagram (Figure 1). It is unclear whether they are coherent with one another (for example, can H2 and H4 logically operate in concert?), and available predictions are lacking specificity (e.g., in the functional form of relations between constructs). In what follows, I turn attention to the dynamical systems approach. I argue that this approach will help to disentangle these myriad hypotheses, generate novel theoretical insights, examine within- and between-person processes longitudinally, and formalize predictions into more falsifiable questions.

4 The Dynamical Systems Approach

A dynamical system is a set of elements (or variables) that change over time by virtue of the connections among them. Relations between the system's elements can be mathematically formalized and computationally simulated to describe how the entire system evolves over time (Martin et al., 2015; Vallacher & Read, 2002). Dynamics—such as the ebb and flow of emotions or cognitive feedback processes in habit formation—are implicit in the ideas of psychology's foundational theorists from James (1890), Lewin (1936), and Asch (1946) to Mead (1934) and Cooley (1902). In fact, some have argued that dynamics are inherent to most psychological and behavioral phenomena (Vallacher, Read, & Nowak, 2002). In more recent decades, psychological scientists have explicitly considered dynamics of cognitive and behavioral processes, and have recognized the potential of computationally simulating systems to improve theory development and testing (e.g., Carver & Scheier, 1982; Heckler et al., 2016; 2018; Martin et al., 2015; van Gelder, 1998; Vallacher & Nowack, 1997; Wiener, 1948/1961). This approach is common to disciplines such as control systems engineering, ecology, and economics, and is starting to take hold in health-behavior research (Spruijt-Metz et al. 2015). Decades ago, Carver and Scheier (1982) argued that symptom monitoring, biofeedback, and medication adherence may be best described by dynamical systems (or similar modeling techniques from cybernetics). Many health-behavior theories tacitly acknowledge dynamics, but few engage with its implications directly, and fewer still attempt to mathematically formalize dynamic predictions (Riley et al., 2016).

The potential for the dynamical systems approach to augment traditional theorizing is staggering (Hekler et al., 2016). First, this approach allows the theorist to

formalize dynamic predictions (e.g., about feedback) or predictions regarding individual-level changes in addition to group-level (average) changes. Second, this approach encourages greater precision and more careful theorizing regarding where, when, for whom, and in what psychological state a theory's mechanism of action will produce an effect. Third, this approach encourages more careful thinking about constructs in one's theory—how they are defined, connected to one another, and change over time. Fourth, this approach stimulates more careful thinking regarding how local theoretical propositions (e.g., beliefs affect behavior) are situated in, influence, and are influenced by the larger human behavioral system (e.g., socio-cultural context, physiology, etcetera.). Fifth, the approach encourages the theorist to make falsifiable predictions by attempting to mathematically formalize and simulate it prior to testing. Sixth, the approach enables theorists to connect theories across disciplines and at different levels of analysis (Tinbergen, 1963). For example, Navarro-Barrientos and colleagues (2011) use a dynamical systems approach to integrate psychological theories (the theory of planned behavior) and physiological theories (energy balance models) in order to better predict weight-loss over time. Seventh, dynamical systems models can help bridge the gap between theory and intervention (Rothman, 2004) by optimizing theoretical models for use in “just-in-time adaptive” interventions (Hekler et al., 2018; Nahum-Shani, Hekler, & Spruijt-Metz, 2015). This is a suite of interventions that adapt over time to a person (i.e., her psychological and physiological state, availability, predisposition, etcetera), with the goal of learning the optimal conditions under which the person responds to interventions, and then delivering them to the person just as they are needed.

In this section, I outline steps involved in a dynamical systems approach to theory development and testing (Figure 2), and touch on just a few of the ways in which it can improve traditional health-behavior theorizing. Steps 1a through 1c are iterated in an initial exploratory phase of research that attempts to develop a theory with clearly falsifiable predictions before experimentally testing it. This phase is the focus of the present research. I then describe why this approach may be generative to theories of sustained behavioral changes in physical activity.

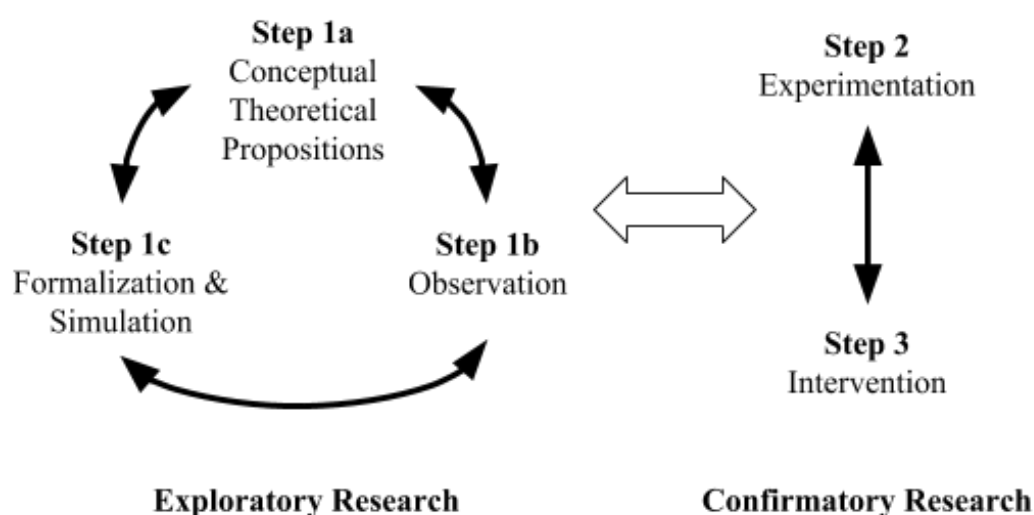


Figure 2: Steps to the dynamical system approach to theory development and testing (1a) reviewing, writing, and diagraming of conceptual theoretical propositions; (1b) observing the real-world behavior; (1c) mathematically formalizing a systems model and simulating it; (2) experimenting on the system; (3) intervening (for similar step-by-step guides see Collins, 2018; Hekler et al., 2018).

Steps 1a and 1b are familiar to health-behavior theorists. In prior sections, I described habitual and motivational constructs that may be particularly predictive of sustained increases in exercise (i.e., processes associated with a person's ability to maintain behavioral changes) based on the extant literature. For example, I proposed that increases in affective judgments about exercise increase automaticity of instigation

behaviors, which helps to perpetuate exercise. I then drew a path diagram of theoretical propositions (Figure 1). The path diagram depicts *unidirectional* relations, similar to the presentation of many other health-behavior change theories. However, a dynamical systems approach requires that iterative processes or feedback is also specified. It presumes that all constructs in one's systems are connected with each other (in some way) as each construct evolves over time. In previous sections, I described how continued exercise may change the nature of motivation and habituation over time, but these iterative processes are absent from the path model in Figure 1. Similarly, most theories of behavior change focus on how psychological predictors (e.g., self-efficacy, automaticity, affective judgments, etcetera.) affect behavioral outcomes (e.g., physical exercise), and give less thought to how behavior, in turn, influences psychological variables or to how this feedback loop evolves over time; though there are exceptions (cf. Carver & Scheier, 2002). One benefit of a dynamical systems approach is that it forces the theorist to consider *iterative processes* (inherent to many psychological phenomena) in greater detail. In addition, moving from conceptual theoretical propositions (Step 1a) to mathematical formulation and simulation of a dynamical system (Step 1c) is conceptually generative for the theorist, for two reasons. First, it expands the set of concepts one can falsifiably theorize about and, second, it highlights system-level consequences of local theoretical propositions.

1.6 Expanding the set of falsifiable theoretical questions.

Moving from Step 1a to Step 1c helps the theorist to think more expansively about what can be theorized about; it expands the set of falsifiable questions that one can ask (for a summary see Table 3). For example, in dynamical systems modeling, the

theorist can mathematically specify: *magnitude* (effect size) and *functional form* (e.g., linear, quadratic) of relations between variables, or how long it takes for one variable to influence another (*time delay*). Additionally, the *time scale* at which phenomena meaningfully change and interact with one another (e.g., weekly) must be considered—which prompts theoretical questions. Do all variables operate on the same time scale? Does aggregating variables to the same time scale change how they affect one another? The *trajectory* of each variable over time is also highlighted. The theorist can ask, what is the expected trajectory of all variables in the system? Do different trajectories across people—say in how affective judgments or automaticity change over time—hold meaningfully different psychological consequences even if those people end up behaving in the same way? The theorist can also consider consequences of different *starting conditions* for each construct in the system. At what level on each construct do we expect the relevant population to be at time zero? How might different starting conditions affect behavior of the system over time?

Table 3. Summary of possible parameters in a dynamical system about which one can theorize

| | |
|----------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <i>Magnitude</i> | The size of the effect of one variable on another. |
| <i>Functional form</i> | The shape of the relation between two variables (e.g., linear, step, quadratic). |
| <i>Time delay</i> | The amount of time it takes for one variable to start affecting another. |
| <i>Time scale</i> | The unit of time at which meaningful changes in a variable are observed under normative conditions. |
| <i>Trajectory</i> | The shape formed by changes in the level of a variable over time (as would be gathered from a time-series plot). |
| <i>Starting conditions</i> | The level at which each variable in the system starts at time zero. In the experimental context, this could be analogous to baseline conditions prior to receiving a treatment. |

Traditional health-behavior theorizing focuses on unidirectional, group-level predictions, and occasionally addresses the magnitude of effects and individual-level processes. Detailed engagement with magnitude and individual-level processes, which is stimulated by the dynamical systems approach, is much less common in the traditional approach. When they are considered, it tends to be implicitly. For example, analyzing longitudinal data with a linear mixed-effects model assumes linear functional form, and allows for inferences at the group- and individual-level. However, theories rarely make explicit whether relations are expected to be linear, or what expectations are for changes at the individual level. In contrast, constructing and simulating a dynamical system brings attention to (and enables testing of) a comprehensive set of potentially important theoretical questions. Questions regarding magnitude of effects, functional form, individual- and group-level changes, and dynamics (or feedback processes) can all be examined under a single methodological and theoretical approach.

There are other methodological approaches that bring theoretical attention to some of these concepts. For example, latent-growth-curve modeling has prompted thoughtful psychological theories on smoking behavior trajectory and identity development (Hertel & Mermelstein, 2012). In particular, adolescent smoking trajectories characterized by rapid increases in smoking frequency over two years (as opposed to gradual or no increase) were associated with stronger smoking identities that increased over time (i.e., thinking of oneself as a smoker escalated). This method speaks to associations between or among group-level trajectory classes and changes in identity over time, but is limited with regard to within-person and dynamic conclusions (e.g., whether increases in smoking identity at time one increases smoking frequency at time two, which increases identity at time three). The dynamical systems approach can also address the within-person and dynamic processes. There are few other approaches that provide such a comprehensive set of conceptual ideas with which the theorist can play, and rest assured that new questions can be formalized and falsified—exceptions include agent-based modeling and computational cognitive models that take a similar approach (Pirolli, 2016; Scalco et al., 2018). In summary, formalizing a dynamical system requires more precision than most contemporary theories of behavior change offer (Riley et al., 2016; Hekler et al., 2016)—a clear opportunity for additional theorizing. The dynamical systems approach not only expands the set of theoretical questions one can consider, but it also increases the precision with which theories are specified and falsified.

1.7 Highlighting system-level consequences of theoretical propositions

Moving from Step 1a to Step 1c also prompts greater consideration of the global (system-level) implications of local theoretical propositions. For example, when the

theorist is solely considering a local proposition (e.g., increases in positive affective judgments increase frequency of exercise) it is hard to imagine how predictions about this small part of the system affect the behavior of the system as a whole. Figure 3 depicts a simple illustration of this idea. When conceptually describing theoretical relations, the theorist is prone to focus on the red and blue paths separately, but neglect how the connection between them (the green path) may alter behavior of the entire system (changes in each phenomenon over time) in a way that fails to meet theoretical expectations. In essence, it is hard to know whether the whole system is the sum of its parts, without summing the parts. Simulation enables the theorist to “sum” distinct theoretical propositions in the system, and to assess whether it results in system-wide behavior in line with expectations.

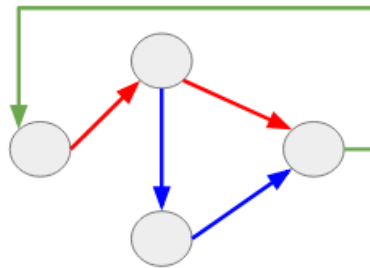


Figure 3. Example of how descriptive theorizing may fail to consider system-level implications of local theoretical propositions

In summary, moving from Step 1a to Step 1c, the theorist attempts to formally define elements of a system (e.g., automaticity and behavior), the time scale at which they operate (e.g., weekly), rules that cover how they interact (e.g., magnitude, functional form, time delays), and then observes the global (system-level) consequences over time. Iterating between conceptual theory and simulation allows for precise refinement of theoretical principles that govern a phenomenon (Hekler et al., 2018). This can be done at

low-cost (i.e., it is easy for a computer to simulate long periods of time), and potentially reduce the cost of conducting longitudinal studies prior to having precise theoretical predictions to guide strong research design. Finally, using a dynamical systems approach to iterate between theory and simulations brings new concepts to the fore that broaden what we even think to theorize *about* when it comes to health behavior change. Carver and Scheier (2002, p. 307) capture the sentiment well, and also foreshadow the difficulty of applying the approach to human behavior:

“The formal nature of the dynamic-systems model lends itself naturally to thinking in quantitative terms, which is desirable. On the other hand, precisely how to operationalize these parameters in behavioral terms poses a challenge to the researcher's creativity.”

5 Present Research

In what follows, I propose a research program that attempts to move theory on processes that sustain behavioral changes in physical exercise from Step 1a and 1b to Step 1c. In Study 1, I draw, mathematically formalize, and simulate a dynamical systems model of the motivational and habitual processes that are predicted to sustain increases in physical exercise. Study 2 is an observational study in which data for all constructs in my dynamical system will be collected among Fitbit users who recently increased their weekly level of moderate-to-vigorous physical exercise. The purpose of Study 2 is to collect data that speak directly to the dynamical systems model, and thus allows for further refinement of the theoretical model. Iterating between theory, simulation, and observation in no particular order is common to this approach (Heckler et al., 2018) and stimulates “creative” hypotheses (McGuire, 1997). Furthermore, obtaining observational

data that are directly relevant to the theoretical model is recommended prior to proceeding with experimentation on dynamical systems (Hekler et al., 2018).

6 Study 1: Drawing, Formalizing, and Simulating a Dynamical Systems Theory of Sustained Changes in Physical Exercise

Adoption of computational and dynamic methods as a way of improving theories is a recent trend in health-behavior research (Rodgers, 2010; Spruijt-Metz et al., 2015). In previous sections, I reviewed conceptual theories and empirical evidence regarding processes that sustain changes in physical exercise. I outlined hypotheses drawn from this literature and drew a path diagram describing theoretical propositions (see Figure 1). In Study 1, I reconceive this conceptual theorizing as a dynamical model using an approach from control systems engineering for modeling how fluids change and flow through a system—a “fluid analogy”—which parallels previous work simulating models of Social Cognitive Theory (Riley et al., 2016) and the Theory of Planned Behavior (Navarro-Barrientos, Rivera, & Collins, 2011). In what follows, I present an initial fluid analogy for processes that sustain increases in physical exercise (diagrammed in Figure 4), the parameters of the model (with brief descriptions), and the system’s differential equations that describe the model (e1 – e5 below). As a part of this study, the initial model will be simulated and refined using MATLAB (Mathwork, 2017). I will then go into more detail on how formalizing the dynamical model can influence conceptual theoretical thinking regarding sustained changes in physical exercise.

1.8 The Fluid Analogy

In the fluid analogy (Figure 4), relevant psychological constructs (e.g., automaticity) are conceptualized as “inventories” with levels that increase or decrease over time based on inflows and outflows. There are five inventories (η_1, \dots, η_5) corresponding to the five variables in Figure 4— affective experience, satisfaction with experience, physical exercise, habitual performance (stability/automaticity), and habitual instigation (stability/automaticity). These inventories are sometimes referred to as “state” or “endogenous” variables in control systems engineering. Inventories have inflows and outflows that represent the influences on these variables over time. For example, an inflow to the inventory for affective experiences (η_1) could be an intervention designed to increase enjoyment of exercise (ξ_1). This type of inflow is sometimes referred to as an *exogenous variable* because it is an influence on the inventory that is external to the system. Inflows can also come from within the system (i.e., paths or “pipes” connecting inventories). The pipes connecting inventories are akin to arrows used to represent regression paths in structural equation modeling (Riley et al., 2016). Each “pipe” connecting inventories has a *resistance* parameter represented by, $\beta_{31}, \dots, \beta_{53}$. Resistances can be thought of as the proportion of the previous inventory that moves into the connected inventory for each instance in time. For example, β_{31} represents the proportion of affect (η_1) that moves into physical activity (η_3). Exogenous variables, such as an intervention on affective judgments (ξ_1), also have resistances, $\gamma_1, \dots, \gamma_5$. In the absence of an empirical basis for resistance parameters, they can be refined through multiple simulations, the results of which are iteratively compared to observational data and/or theoretical expectations before formal experimentation (Riley et al., 2016).

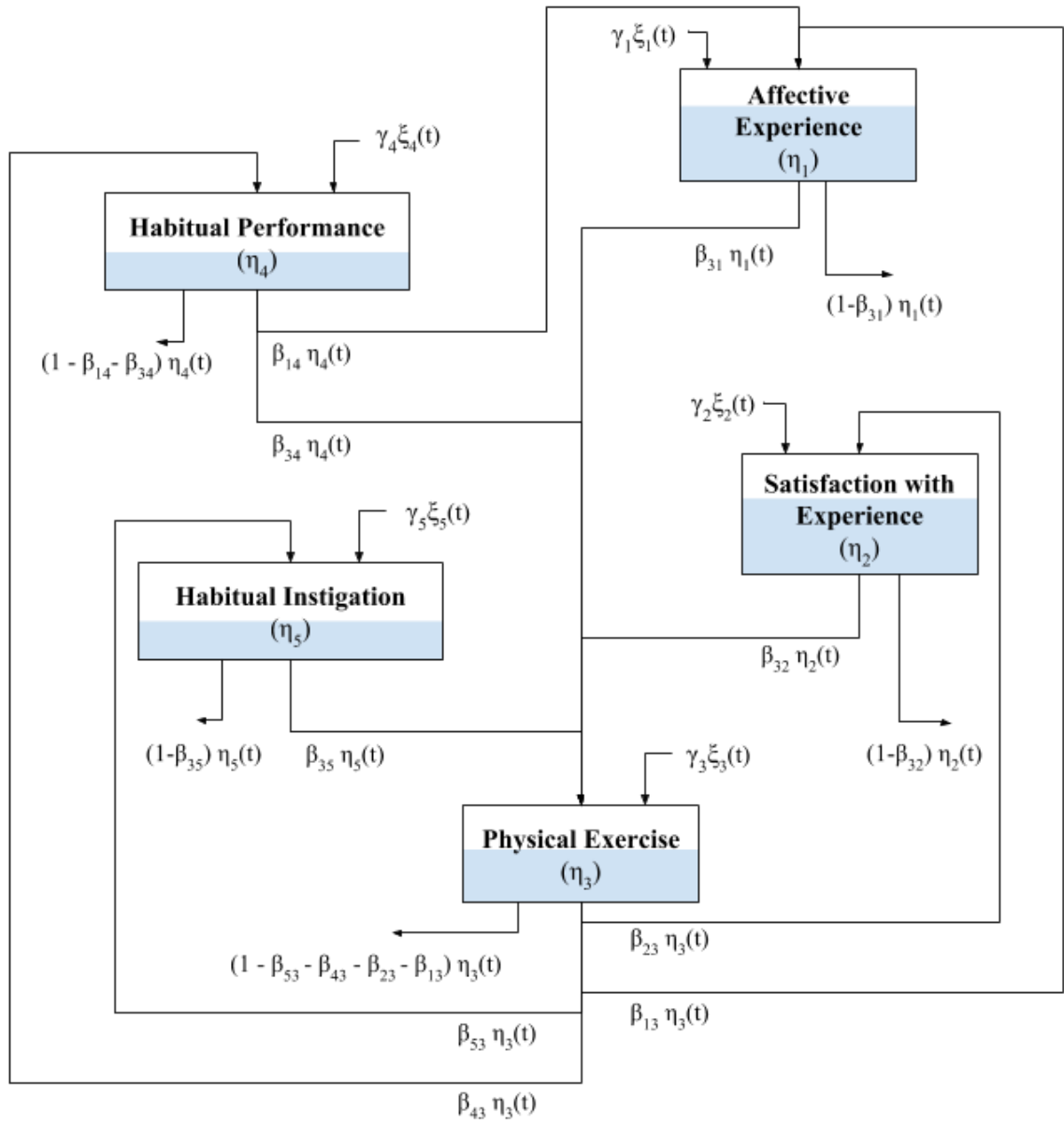


Figure 4. Dynamical systems model of processes that sustain increases in physical exercise using a fluid analogy

Additional parameters can also be explored in simulations of dynamical systems, but are excluded from this version of the model to simplify simulations. For example, Riley and colleagues (2016) also simulated *time delays* and *disturbances* in their dynamical model of social cognitive theory. Using the fluid analogy, time delays can be thought of as the time it takes for fluid from one inventory to traverse the pipe to another inventory. *Disturbances* are unmodeled dynamics that can be thought of as way to introduce noise or error into the model.

Finally, the present dynamical model follows the approach of Riley and colleagues in applying the principle of *conservation of mass* to each inventory. Specifically, accumulation in each inventory (the level of the variable) corresponds to the net difference between the inflows and outflows. This results in a rate of accumulation that is the multiplicative product of *time constants* (τ_1, \dots, τ_5) and the rate of change (derivative, e.g., $\frac{d\eta_1}{dt}$) in the level of the inventory (see differential equations below). Time constants represent the capacity of the inventory and allow for exponential decay of the inventory to accommodate the natural decay of initial changes in behavior (i.e., the tendency for behavior to return to baseline after changes). Using our analogy, the inventory for exercise is “leaky.” Changes in the level of exercise is expected to naturalistically decline over time. The following system of differential equations (e1 - e5) describes dynamics of inventories in the model (Figure 4):

$$(e1) \quad \tau_1 \frac{d\eta_1}{dt} = \gamma_1 \xi_1(t) + \beta_{13} \eta_3(t) + \beta_{14} \eta_4(t) - \eta_1(t)$$

$$(e2) \quad \tau_2 \frac{d\eta_2}{dt} = \gamma_2 \xi_2(t) + \beta_{23} \eta_3(t) - \eta_2(t)$$

$$(e3) \quad \tau_3 \frac{d\eta_3}{dt} = \gamma_3 \xi_3(t) + \beta_{31}\eta_1(t) + \beta_{32}\eta_2(t) + \beta_{34}\eta_4(t) +$$

$$\beta_{35}\eta_5(t) - \eta_3(t)$$

$$(e4) \quad \tau_4 \frac{d\eta_4}{dt} = \gamma_4 \xi_4(t) + \beta_{43}\eta_3(t) - \eta_4(t)$$

$$(e5) \quad \tau_5 \frac{d\eta_5}{dt} = \gamma_5 \xi_5(t) + \beta_{53}\eta_3(t) - \eta_5(t)$$

1.9 *Consequences for conceptual theorizing for sustained changes in physical exercise*

In this section, I will expand upon the set of falsifiable theoretical questions that can be assessed using the dynamical systems approach and simulation of the fluid analogy, and demonstrate how they may be relevant to theorizing about changes in exercise. In general, this approach requires thinking in more detail about the particular context in which a theory is relevant. In this case, I will focus on a context in which healthy adults have recently attempted to increase their level of moderate-to-vigorous exercise, and have been able to sustain this change for a short period of time, one to three months. At this point it may be evident that in order to specify a dynamical systems model and run simulations, the theorist must have a strong grasp of the particular context of interest—which could be a particular study design and method. Study 2 (detailed below) goes hand-in-hand with Study 1 in that assumptions in the simulation are associated with decisions in the design and methods of Study 2. For example, assumptions regarding start conditions of the simulation correspond to decisions regarding recruitment population and eligibility criteria of Study 2. In what follows, I explore how formal simulation spurs new thinking about processes that sustain changes in exercise.

1.9.1 **Naturalistic Entropy or Decay**

As discussed previously, thinking of human behavioral patterns (e.g., one's pattern of exercise) as a dynamical system, the function of which depends upon many constituent parts interacting with one another over time, highlights that decay of any change to the system is probable (Pinker, 2018; Tooby et al., 2003). Any attempt to increase frequency of exercise will require energy to fight against natural decay. For example, one regular UK poll on New Year's Resolutions found in 2015 that 36% of people attempted to increase physical activity, a majority of whom failed to maintain those changes, with over 60% quitting within one month (ComRes, 2015). Energy in the form of changes in motivational or habitual processes can help spur or prevent decays in exercise after a change is made. As mentioned above, time constants in the initial model (Figure 4) represent the capacity of the inventory and allow for exponential decay of the inventory to accommodate the natural decay of initial changes in behavior. Taking a dynamical systems approach highlights the need to explicitly specify that natural decay in exercise is expected after a change is attempted.

1.9.2 Time Scale

In order to simulate a dynamical systems model, one must specify the time scale at which variables in the system are operating (e.g., weekly). Time scale describes the unit of time at which *meaningful* changes in a construct occur under *normative* conditions or in a particular context (Heckler et al., 2016). For example, heart rate is often scaled at beats per second or beats per minute because fluctuations at these units are considered meaningful. Similarly, the appropriate time scale for a construct such as the built environment (e.g., bike paths in a city) may be on the order of years. Under normative conditions, it takes years for bike paths in a city to meaningfully change. However, note

that it is possible for bike paths to meaningfully change at a faster rate (e.g., months) when conditions are non-normative (in a particular context), such as during a citywide bike-lane construction initiative. What is the appropriate time scale for variables in my model? In other words, for each of the five variables in the model, at what time scale do we expect to observe meaningful fluctuations in the particular context of interest?

These questions highlight the need to have a basic understanding of how constructs might be operationalized in order to make predictions about the time scale on which they operate (which is articulated in the measures section of Study 2). They also highlight the need for observational longitudinal data that can speak directly to this question for each variable. However, we can also theorize in the abstract about what we might expect for each variable. Starting with exercise, we may want to define meaningful changes as changes relevant to meeting national physical activity guidelines, because these are based on activity levels associated with better long-term health outcomes (i.e., lower risk of all-cause mortality, coronary heart disease, stroke, etc.). National guidelines are often defined on a *weekly* time scale, for example, in the U.S.A. the current recommendation is as follows (USDHHS, 2018):

“For substantial health benefits, adults should do at least 150 minutes (2 hours and 30 minutes) to 300 minutes (5 hours) a week of moderate-intensity, or 75 minutes (1 hour and 15 minutes) to 150 minutes (2 hours and 30 minutes) a week of vigorous-intensity aerobic physical activity, or an equivalent combination of moderate- and vigorous-intensity aerobic activity. Preferably, aerobic activity should be spread throughout the week.”

Perhaps the week is also the most meaningful time scale (and chosen for national guidelines) because it is the most psychologically meaningful scale. In other words, it is easiest for a human to take mental account of (or self-monitor) whether her/his level of physical activity in any given week is higher or lower relative to one's general weekly tendency. This may be much harder on an hourly, daily, monthly, or yearly scale.

Perhaps, also, meaningfulness of the time scale is defined by the level of the system as a whole or the particular context of interest (i.e., processes that sustain changes in exercise). It is worth noting that dynamical systems models are much easier to formalize and interpret when all constructs in the system are operationalized on the same time scale (Rivera, 2018). If sustaining changes in exercise long-term is the critical context in which the system is operating, perhaps people are most likely to judge whether they have sustained recent increases in physical activity at the weekly scale, as opposed to smaller times scales (e.g., hours or days). Though, using this logic, larger time scales may also be meaningful (e.g., monthly). This type of thinking can be applied to each of the constructs. Affective experiences, for example, might fluctuate daily. However, those fluctuations may fail to hold meaning for whether a person sustains increases in physical activity. This type of thinking is stimulated when attempting to simulate a dynamical system, and I apply this logic to the decision to use a weekly time scale in the planned simulations (Study 1) and data collection (Study 2).

Taken together, the dynamical systems approach encourages a focus on time scale. Health-behavior change theories are rarely explicit in their discussion of the appropriate time-scale on which constructs are expected to operate (cf. transtheoretical model), thus the dynamical systems approach highlights potentially interesting theoretical

questions regarding time (Dormann & Griffin, 2015; Scholz, 2019), and can help make theoretical predictions more specific (George & Jones, 2010). It is evident from the above exercise that this approach is challenging,⁴ and in the absence of direct empirical evidence for setting a certain time scale, the precedent of prior research and the theorist's intuition are all we have. In the end, the approach forces more careful thinking about the time scale relevant to one's theory and encourages justification for those decision prior to collecting data. Furthermore, simulation may reveal that variables in one's model do not change in the expected ways at the set time scale, which may be reason to consider making changes to one's theory.

1.9.3 Functional form and trajectories

Simulation of dynamical systems also brings greater theoretical focus to functional form and trajectories. Functional form is the type of relation (e.g., linear, quadratic, step) *between* constructs in the system. Say, for example, physical activity (x) is associated with affective judgment (y) such that $y = x^2$. This describes a quadratic functional form between affective judgment and physical activity. In contrast, trajectories describe how the level of each construct in the system changes over time. For example, repeated measurement of physical activity could result in a linear trajectory such that a one unit increase in physical activity corresponds to a one unit increase in time. The dynamical systems approach forces the theorist to think carefully about these concepts,

⁴ Rast and colleagues (2012) capture the sentiment well: "Change is a within-person process that occurs at different rates and at different points in time for different people. As such, within-person change may not be well captured by static, widely spaced multiwave designs - even more so for nonnormative change, such as disease-related cognitive decline, where it is hardly possible to define a priori the most adequate sampling interval for each individual."

because functional form must be specified and trajectories of each variable in the system is a result (output) of the simulation. How might these concepts be applied to theorizing about sustaining increasing in exercise?

First, there is some empirical evidence that as exercise is repeated over time, automaticity of exercise has an asymptotic trajectory. Lally and colleagues (2010) asked participants to try to keep a new exercise routine for roughly three months over which they observed an asymptotic trajectory of automaticity for the new behavior: The initial change led to rapid increases in automaticity that gradually decelerated over time. Peak automaticity for physical activity was reached after a median of 90 days. Similarly, in a longitudinal study of exercise habit formation, Kaushal and Rhodes (2015) observed a similar asymptotic peak in automaticity after maintaining the same behavior for 6 weeks. From these studies and other reviews (e.g. Rebar et al., 2018) the trajectory of automaticity appears to be reliably asymptotic; however, these studies reveal considerable variability across people in the amplitude of and latency to peak-automaticity. Simulations of a dynamical systems encourages this type of theoretical thinking and observational research.

Thinking about trajectories also stimulates theorizing about the likelihood that any changes in the systems (or one's exercise) are maintained under normative conditions. In fact, as has been discussed previously, behavioral systems may be similar to physical systems, in that there is a general tendency for decay over time, or at least there is a pull toward baseline levels of the system after any changes are made. This aligns well with the observation that initial changes in behavior are hard to maintain and often return to baseline levels at an exponential rate (Tobias, 2009), similar to that of memory and

learning models (e.g., the forgetting curve; Woźniak et al., 1995). This type of theorizing is embedded in model simulation, and as stated earlier, an assumption of exponential decay of exercise over time is specified in my model.

1.10 Planned Simulation

Running this type of simulation results in time-series plots for each of the variables in the system, which I will refer to as “scenarios.” In other words, the outcomes of each simulation are data that describe behavior of the entire system over a specified period of time (at a particular time scale), and are depicted in time-series plots.

Simulations can be used to develop and refine a model by comparing the resulting scenarios to theoretical expectations or observational data (e.g., Riley et al., 2016). For example, Figure 5 depicts a scenario that could describe relations in Hypothesis 3a: Increases in habitual processes in performance undermine motivational processes, which may result in failure to sustain exercise, particularly when habitual instigation decreases.

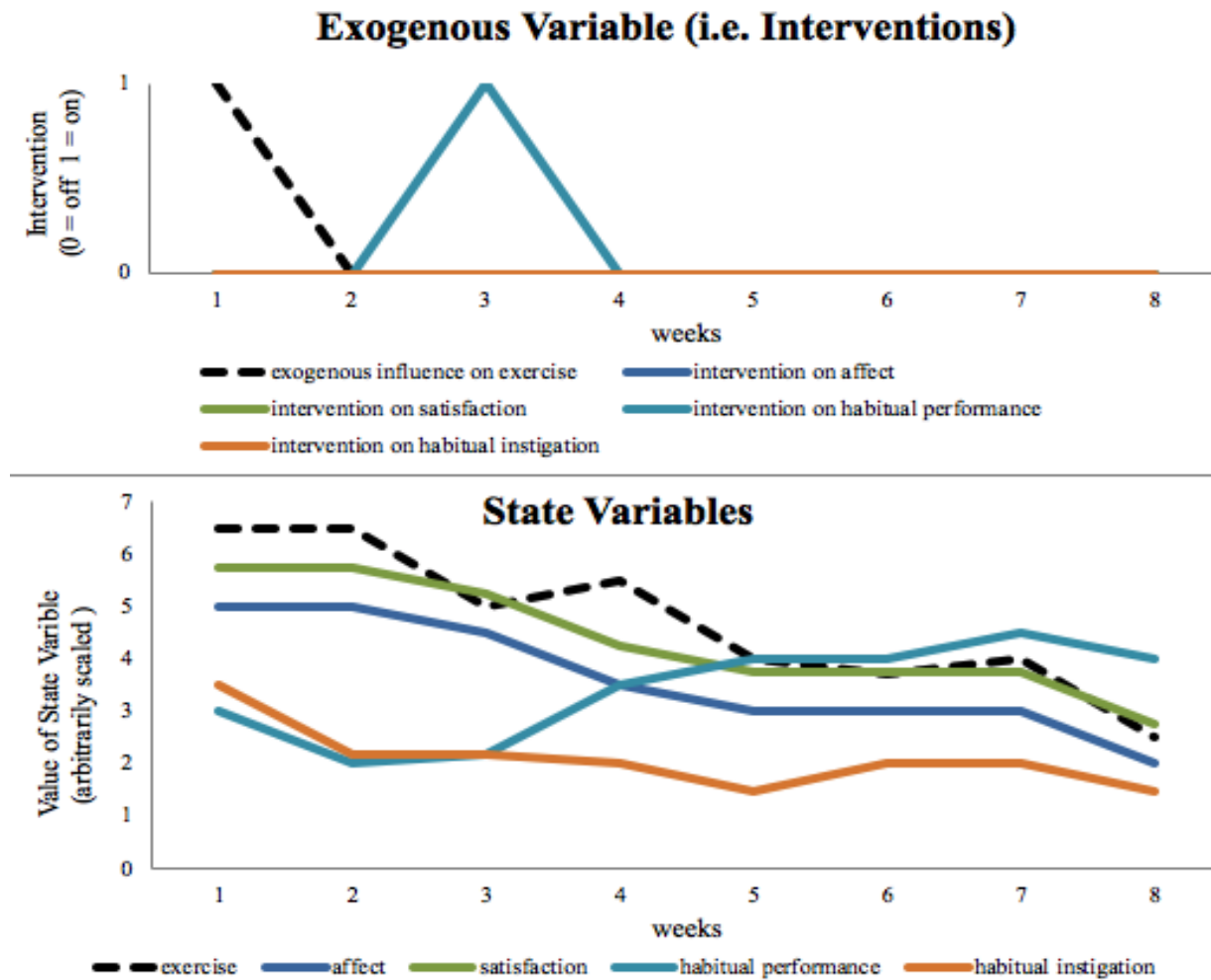


Figure 5. Hypothetical Scenario Associated with Hypothesis 3a

The bottom panel of Figure 5 depicts hypothetical changes over eight weeks (x-axis) in the value (y-axis) of each state variable in the system (i.e., a person's physical exercise, affective experience, satisfaction with experience, habitual performance, and habitual instigation). The value of each state variable on the y-axis is arbitrarily scaled from 0 = low (or negative) to 7 = high (or positive). Scenarios describe the "behavior" of the system. In this case, all state variables gradually decline in value over time, except for habitual performance, which gradually increases. The top panel of Figure 5 depicts whether or not exogenous variables are activated (i.e., variables are either 0 = off/deactivate; 1 = on/activated). As discussed previously, exogenous variables are external influences on state variables (inventories) in the system, and in the context of health behavior research, can be thought of as interventions. In this scenario an intervention on habitual performance is active in Week 3. This intervention could take the form of information about how to routinize one's exercise program (e.g., helping people pick an exercise they enjoy and do it the same way each time; Kaushal et al., 2017).

This scenario also assumes certain starting conditions (i.e., the value at which each state variable commences). In particular, it assumes that at Week 1, people have relatively high levels of exercise, affect, and satisfaction, and middling levels of habitual performance and instigation. The reason for this assumption is related to the particular context of interest: What happens after people make initial increases in their physical exercise? Thus, if this scenario were to describe a longitudinal observational study, the starting conditions are presumed to be participants' psychological state upon enrollment in the study. This scenario could describe a study in which participants are recruited from a population of people who recently initiated increases in physical exercise (thus the high

starting values for physical exercise). Furthermore, note that an exogenous influence on exercise is active in Week 1. Here, I am assuming that a variable external to the system (i.e., enrollment in the study) will temporarily increase physical exercise.

To conclude this section, I will further elaborate on the scenario presented in Figure 5 and how it maps on to Hypothesis 3a. Study 2 attempts to recruit people who successfully increased their physical exercise within the last three months (see Study 2 methods below). This is reflected in the starting conditions of the simulation. Participants are enrolled in a study on physical exercise at Week = 1, which tracks changes in motivational and habitual processes in addition to physical exercise. Simply enrolling in the study may influence a person's physical exercise reflected by activation of the exogenous influence on exercise (at $x = 1$), which results in high levels of exercise over the following two weeks. In this scenario, something happens to increase habitual performance at week three (an intervention on habitual performance is activated or a naturally occurring external influence is activated), which results in a gradual increase in habitual performance (depicted by the turquoise line in the bottom panel from Week 3 to Week 8). Additionally, Hypothesis 3a expects the sole increase in habitual performance to result in decreases in motivational variables (blue and green lines). These changes are guided by relations between state variables, which are reflected in the simulation by parameters such as *resistances*, $\beta_{31}, \dots, \beta_{53}$. Finally, because habitual instigation also decreases in this scenario (orange line), it is expected that levels of physical exercise will decline (dashed black line in bottom panel), resulting in a failure to sustain initial increases in exercise. These changes are also guided by relations between state variables reflected in the simulation parameters.

The model parameters described above will be refined, new parameters added, or exogeneous inputs manipulated until the resulting scenarios match hypothetical scenarios. In other words, the aim of these simulations is to identify a set of parameters and inputs that result in scenarios that align with theoretical hypotheses set forth above. If it is not possible to define parameters or manipulate inputs in a way that match hypothetical scenarios, parameters may be added or removed until expectations are met. Furthermore, if the resulting set of parameters is unrealistic, additional changes may be made to model. For example, time delays could be added as a parameter in line with the research of Riley and colleagues (2016). Finally, observational data will be collected in Study 2 and used to continue refining model parameters. Simulations will be concluded when the theorist decides that parameters and resulting scenarios adequately represent theoretical expectations and observational data. The process is exploratory and is up to theorist's judgment based on visual comparisons between observation and simulation output to determine whether the model is adequate. There are no inferential statistics or decision criteria to guide this process. For more definitive results that can confirm the validity of one's dynamical systems model, one must conduct a system identification experiment (Heckler et al., 2018), which is beyond the scope of the present research.

Results from the simulation after considering results from Study 2 are presented below, following the discussion of Study 2.

7 Study 2: Observational Longitudinal Study

Any attempt to improve upon traditional health-behavior theories of physical activity using a dynamical systems approach requires the collection of intensive longitudinal data (Dunton & Atienza, 2009; Nahum-Shani, Hekler, Spruijt-Metz, 2015). Intensive longitudinal data are rich in number of measurement occasions, which enable within-person, dynamic, and computationally expensive analyses (Bolger & Laurenceau, 2013). The rise of new technologies over the last two decades—smart phones and wearable sensing (Kumar et al., 2013)—in conjunction with new methodologies such as ecological momentary assessment (Dunton, 2017), have reduced burden on participants, lowered costs of collection, and increased availability of intensive longitudinal data (Spruijt-Metz et al., 2015). Furthermore, there is consensus among experts that “observational studies of the natural history of successful long-term behavior change” are needed to understand more fully what enables people to sustain healthy levels of physical exercise (Wing, 2000, p. 84). Naturalistic, intensive, longitudinal, observational data are also key to early-phase research and theorizing using the dynamical systems approach (Hekler et al., 2018). The approach helps move theories from broad conceptual models focused on interpersonal variability and unidirectional processes to more specific predictive models that also consider intrapersonal variability and dynamics. Prior theorizing highlights the importance of motivational and habitual processes to sustaining changes in physical activity. The aim of the current study is to collect data that can refine the dynamical systems model of Study 1, and to inform more nuanced theorizing on processes that sustain changes in physical exercise. Fitbit users who increased their level of exercise over the last three months will be recruited, and then naturalistically followed

for two months as they answer regular surveys on motivational and habitual processes that may help them successfully sustain the increased activity.

1.11 Physical exercise in the U.S. with Fitbits

For healthy adults living in the U.S., the Department of Health and Human Services recommends 150-300 minutes per week of moderate-intensity aerobic physical activity, 75-150 minutes per week of vigorous-intensity, or the equivalent combination, ideally spread out over the course of the week (USDHHS, 2018). Increasing activity level to meet this objective for a single week is a challenge for most Americans (Piercy et al., 2018), let alone sustaining it for months. Authors of U.S. national guidelines and many other researchers believe the best way for most Americans to meet these standards, and to achieve long-term health benefits, is to try to perform a total of 20-30 minutes of leisure-time cardiovascular exercise every day, in at least 10-minute bouts (Moore, Patel, & Mathews, 2012; USDHHS, 2008, 2018). Cardiovascular exercise is physical activity that noticeably increases a person's heart rate for at least 10 minutes. This can be accomplished in many ways, for example, running, biking, lifting weights, brisk walking, or playing sports. Many people have purchased wearable devices to motivate themselves to be more active and to monitor whether they have met suggested standards. In fact, the Fitbit app and dashboard are designed to highlight activity achievements and to encourage goals that align with U.S. national guidelines. Fitbit is among the market leaders in wearable activity trackers with an estimated 9.5% market share worldwide in quarter two of 2018 (IDC, 2018), and an estimated 25.37 million "active users" in 2017 based on public exchange filings, most of whom are in the U.S. (Fitbit, Inc., 2018). In

addition to meeting reliability standards for assessment of physical exercise (see measures section), there are many active Fitbit users from which to recruit for research.

1.12 Assessment of Motivational and Habitual Processes

As discussed extensively in Section 3, the health behavior literature focuses on two constellations of processes that are hypothesized to help sustain increases in physical exercise: motivational and habitual. In what follows, I provide additional detail on these constructs that will be the focus of the present research.

Study 2 focuses on two motivational constructs— affective experiences and satisfaction with experience. Assessment of affective experience in physical exercise vary widely in focus and psychometric properties (for reviews see Chmielewski et al., 2016; Rhodes et al., 2009). A recent review and psychometric evaluation of many motivational constructs for physical exercise concluded that the Enjoyment/Interest Subscale of the Motives for Physical Activity Questionnaire-Revised (MPAM-R-E; Ryan et al., 1997), and the Intrinsic Regulation Subscale of the Behavioral Regulation in Exercise Questionnaire-2 (BREQ-2-IR; Markland & Tobin, 2004; Mullan, Markland, & Ingledew, 1997) were the most psychometrically sound. In other words, these two measures had the most robust dependability, discriminant validity, and criterion validity. In contrast to measures of affective experience, satisfaction with experience is usually assessed with a single item focused on global satisfaction with outcomes that may have resulted from making a change to one's level of physical exercise (Baldwin & Sala, 2018; Baldwin et al., 2006). There are, however, multi-item assessments of satisfaction that are sometimes used in exercise research, for example, the Modified Reasons for Exercise Inventory (mREI; Cash, Now, & Grant, 1994; Chmielewski et al., 2016; Sears & Stanton, 2001). In

Chmielewski and colleagues' review, single-item measures of satisfaction and the mREI were not as psychometrically sound as the MPAM-R-E and BREQ2-IR. However, there were limitations to the review, the most relevant of which concerns a distinction between *in general* evaluations of one's typical physical exercise, and *in particular* evaluations of a specific exercise episode or series of episodes in the recent past. In the review, single-item satisfaction and the mREI were assessed *in general*, but these scales were originally developed for application to a particular context in which a person is attempting to maintain increases in their physical exercise. Thus, *in particular* assessments of these scales focused on the context of maintaining changes—the approach of the present research—may be more predictive and psychometrically valid.

Study 2 also focuses on two habitual processes—context stability and automaticity. Both of these will be measured separately for two sub-actions of physical exercise: *instigation* (e.g., deciding to exercise) and *performance* (engaging in an action as a part of exercising, such as pedaling a bike). In what follows, I briefly review the history of assessing habitual processes specific to physical exercise, and justify the approach taken in the present research.

In early research, past behavioral frequency was often used as a measure of habitual processes (e.g., Bagozzi, 1981), in part, because it is such a strong predictor of future behavior (Aarts, Verplanken, & Knippenberg, 1998; Ouellette & Wood, 1998; Verplanken, 2010). However, many have argued that this measurement approach is unsatisfactory. It is largely based on the lay notion of habit as regular, frequent, or persistent behavior, and lacks explanatory value and discriminant validity (Aarts & Dijksterhuis, 2000; Gardner, 2015; Rebar et al., 2018; Verplanken, 2010). Furthermore, a

meta-analysis of the association between past and future behavior highlighted that the relation is strongest for behaviors that were executed frequently and consistently in the same context (Ouellette & Wood, 1998). Spurred by these findings, Wood and colleagues (2005) recommended that habit strength (i.e., habitual processes) be measured with a combination of past behavior frequency and context stability (i.e., what I refer to as the “context-stability” approach). Using this approach, Tappe and Glanz (2013) developed a popular index specific to physical exercise, the Exercise Habit Survey (EHS). From this perspective, habits are formed when a behavior is paired with a particular contextual cue many times, at which point the behavior operates automatically whenever the cue is present.

The context-stability approach to studying habitual processes is common in social and health psychology; however, there is considerable debate over whether this measurement approach is satisfactory, particularly in the context of complex behaviors such as physical exercise. Some argue that it is inadequate because it presumes that the behavior operates automatically when a behavior is frequently observed in a consistent context, which may not always be the case (Gardner, 2015). For example, performing an unfamiliar but simple task (counting the number of times “she” appears in a text) results in a stronger habit immediately afterwards than does engaging in a more complex task (counting the number of references to mammals or movable objects), despite identical behavioral repetitions in an unchanging context (Verplanken, 2006). These results cast doubt on the assumption that habitual processes are solely a consequence of context stability, particularly for more complex behaviors.

Verplanken and Orbell (2003) proposed a self-report habit index (SRHI) to address this critique of the context-stability approach. They propose that habitual processes consist of three conceptual parts: (1) the experience of repetition (i.e., frequency), (2) lack of awareness, lack of control, or mental efficiency (i.e., automaticity), and (3) identity, which the authors later claim was mislabeled, and more accurately reflects repetitiveness of the experience (Orbell & Verplanken, 2015). The SRHI assumes that people can be aware, when reflecting on their behavior, that they were unaware when performing it. For example, the SRHI assumes that an experienced driver who regularly buckles her seatbelt may accurately report a lack of awareness of doing so. Still, some question the validity of this assumption (cf. Hagger et al., 2014). Furthermore, others question whether the behavioral frequency items in the SRHI should be included at all (e.g., Rhodes et al., 2010), as including behavioral frequency in both the predictor and the outcome is problematic (Gardner et al., 2011; Sniehotta & Pesseau, 2012). This has led some to focus on a subscale of the SRHI comprised of only the automaticity items (the SRBAI; Gardner et al., 2012). Rebar and colleagues (2018) concur with this approach, stating that if the objective is to estimate the relation between habitual processes and behavior, it is important to ensure habitual and behavioral constructs are distinct. Furthermore, they argue that even though measures of habitual processes are likely correlated with past behavioral frequency, they should not be equated with frequency history because an action can be frequently performed in a consistent context without being automatic, such as a doctor frequently suggesting an operation, which few would characterize as a habit.

Despite ongoing debates around measurement of habitual processes, all three approaches—context stability/EHS, SRHI, and SRBAI (automaticity subscale of SRHI)—seem to have reasonably strong psychometric properties and are predictive of physical activity (Gardner et al., 2011; Gardner et al., 2012; Tappe & Glanz, 2013; Verplanken, 2006; Verplanken & Orbell, 2003; Wood & Neal, 2007). Furthermore, several of these authors have conceded that both context stability and automaticity are likely important to understanding habitual processes in physical exercise (e.g., Orbell & Verplanken, 2015); thus, the present research attempts to measure both of these constructs.

1.13 Exploratory hypotheses for Study 2

As discussed previously, the extant literature suggests that positive affective experiences, satisfaction with experience, context stability, and automaticity are critical to sustaining changes in physical exercise. Prior theories have suggested that a maintenance phase (dominated by motivational processes) proceeds and is distinct from a habit phase (dominated by habitual processes). I presented empirical support that motivational processes and habitual processes are relevant across phases of behavior change, at least for complex behaviors (such as physical exercise), which involve many distinct sub-actions (such as instigation v. performance).

Here I revisit hypotheses derived from the literature with a focus on how to think about them from a dynamical systems perspective. In particular, what might the trajectory of each variable look like? And how is the resulting pattern of change for each variable (each scenario) related to these hypotheses? Note that affective experience and satisfaction similarly affect sustained activity across hypotheses, thus I collapse them

here into a single motivational construct to simplify discussion. Automaticity and context stability are also collapsed into a habitual construct for the same reason. Thus, hypotheses focus on how motivation, habitual instigation, and habitual performance (collectively referred to as “variables” below) interrelate to affect sustained physical exercise, and are presented in Figure 6. The hypothetical scenarios of Figure 6 represent what might unfold for two months after people initiate an increase in their level of exercise over the prior two months. Furthermore, here, I attempt to group hypothetical scenarios into classes—whether scenarios will result in maintenance of physical exercise (success) or whether exercise levels will decay over time (failure).

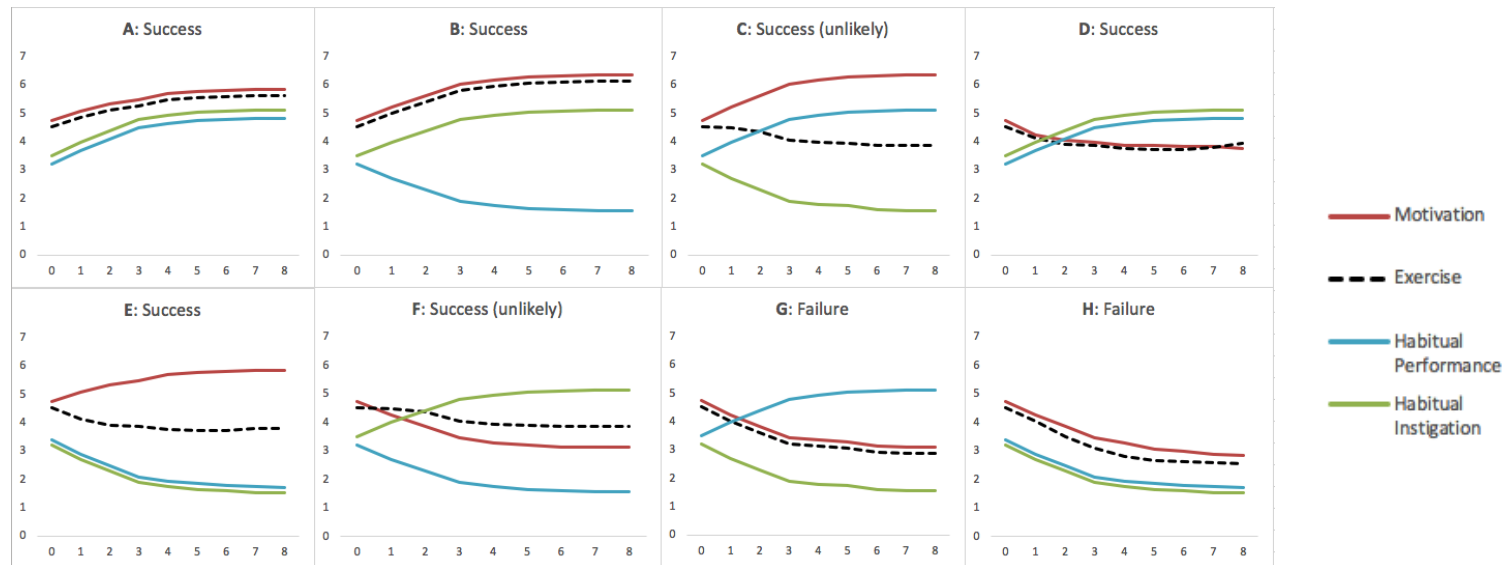


Figure 6. Hypothetical scenarios (A-H, above) and hypotheses table (below) for maintenance success and failure

Note: For scenarios, the x-axis is weeks in the study, and the y-axis is arbitrarily scaled for each variable. The below hypotheses are mapped onto hypothetical scenarios that could reasonably represent supportive, unsupportive, or ambiguous evidence for the hypothesis.

| Hypotheses derived from available literature | Representative Scenario(s) | | |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|---------------------|------------|
| | Supportive | Unsupportive | Ambiguous |
| Hypothesis 1: Higher levels of motivation will help people maintain increases in exercise over two months. Additionally, higher levels of habitual variables, for both performance and instigation, will also help people to maintain increases in physical exercise over two months. | A, D, H | B, C, E, F, G | none |
| Hypothesis 2: Motivational processes positively affect habitual processes, particularly instigation, which positively affects sustained behavior. | A, B, G, H | C, E, F | D |
| Hypothesis 3A: Habitual processes in performance undermine motivational processes, which may result in failure to maintain behavior. | G | A, C, F | B, E, D, H |
| Hypothesis 3B: Yet, habitual processes in performance make it easier to do the behavior, which may help to maintain it. | A, C, D, H | B, F, G | E |
| Hypothesis 4: Increasing habitual processes in instigation while maintaining mid-to-low levels of habitual processes in performance is most likely to maintain behavioral changes (Type 2 Habitual Behavior from Table 2). | B | A, C, D, E, F, G, H | none |

First, Scenarios A through H are ordered from most successful to most unsuccessful maintenance. In Scenario A, all variables increase (asymptotically) over time, which is expected to result in successful maintenance. This scenario aligns with Hypotheses 1, 2, and 3b. This scenario misaligns with Hypothesis 3a, which states that higher levels of habitual performance undermine motivation. If this were true, we would expect that the trajectory of motivation (in red) might dip as habitual performance (in blue) increases. However, in Scenario A both constructs increase over time at a similar rate.

In Scenario B, motivation and habitual instigation increase (asymptotically) over time, while habitual performance is at mid-to-low levels by Week 4, resulting in successful maintenance, and potentially, increases in physical exercise. This scenario perfectly aligns with predictions from Hypothesis 4. It also aligns with Hypothesis 2 (because motivation and habitual instigation vary together), and Hypothesis 3A.

Scenario C is the same as Scenario B, except the trajectories of habitual instigation and performance are swapped. This is expected to result in successful maintenance of physical activity, but at lower levels. Given my set of hypotheses, Scenario C is unlikely to be observed because none of the hypotheses directly support it, and two of them (H2 and H3) contradict such behavior.

In Scenario D, habitual instigation and performance hang together and increase over time, whereas there is a slight dip in motivation (but middling levels are maintained). This is expected to result in successful maintenance, such that similar levels of physical exercise are maintained throughout. This scenario aligns most strongly with

Hypotheses 1 and 3b: All variables remain at relatively high levels supporting maintenance, and habitual performance is also supportive. Furthermore, this scenario could potentially describe Hypothesis 2 and 3a, though not perfectly. Motivation and habitual instigation covary somewhat, and when habitual performance is at higher levels, motivation begins to dip.

In Scenario E, motivation increases slightly as habitual performance and instigation decline together. This might result in a slight reduction in physical exercise over time, but the original level is still successfully maintained. This scenario could represent Hypothesis 3A, but misaligns with Hypothesis 2.

In Scenario F, habitual instigation increases as habitual performance and motivation decrease. This might result in a slight reduction in physical exercise over time, but the original level is still successfully maintained. This scenario is unlikely given the hypotheses because it misaligns with Hypothesis 2, and is not directly supported by any other hypotheses.

In Scenario G, habitual performance increases as motivation and habitual instigation decreases, resulting in decreases in physical exercise and a failure to maintain original levels. This scenario aligns best with Hypothesis 2 and 3a, because motivation and habitual instigation covary, and higher levels of habitual performance undermine motivation. This scenario is related to Scenario B. It describes similar system behavior (in that the constructs are related to each other in a similar way), except in this case, the result is failure to maintain physical exercise as opposed to successful maintenance.

In Scenario H, all variables decline (asymptotically) over time, which results in a failure to maintain physical exercise. This scenario aligns best with Hypothesis 1 and 2: All variables are positively related to behavior, and motivation and habitual instigation hang together.

Study 2 explores the veracity of these eight scenarios and their relation to the four hypotheses derived from the literature. Data were collected from Fitbit users who recently increased their physical exercise, and Study 2 explores how each of these variables changes over the course of two months. Two exploratory analytic approaches are then used to help better understand operation of my dynamical system and to refine theories for processes that sustain physical activity.

Specifically, Study 2 uses an intensive measurement longitudinal design (Rast et al., 2012). Participants who recently increased physical exercise were recruited, and followed for eight weeks during which exercise was tracked and motivational and habitual processes were regularly assessed. Earlier discussion of the dynamical systems approach highlights the importance of carefully articulating the expected starting value of each variable in the system. In other words, in what state are participants entering the study? I am interested in sampling a population of people who have recently increased their physical exercise and who are in a critical “maintenance” period in which they are attempting (and may be struggling) to maintain those changes long-term. I determined that recruiting people who increased physical exercise sometime over the last two months, followed by eight weeks of observation adequately captures this critical period. It was expected that this critical period would result in enough variability in intra- and inter-individual trajectories in physical exercise, motivation, and habitual variables to

draw meaningful insights. For example, I expected that observing participants during this period would result in a mix of those who successfully maintained a higher level of physical exercise and those who did not. This is based on prior literature indicating that initial changes in physical activity start to return to baseline levels within weeks (Rhodes et al., 2009). Additionally, fitness benefits tend to be realized around two months of initiating a new exercise program (Colcombe & Kramer, 2003). Thus, those who were able to maintain increases in exercise for the duration of the observation period would have likely made a clinically meaningful change.

1.14 Methods

1.14.1 Registration, Open Materials and Data

Registration of Study 2 took place during participant recruitment and data collection, but prior to any data analysis (osf.io/bde6g). All measures are reported. See Appendix A for questionnaires, stimuli, and instructions, and the project page at osf.io/my3w9 for other materials.

1.14.2 Participants

Participants were recruited on a rolling basis through social media, web ads, activity tracker forums, research participant pools, flyers, fitness centers and gyms, and university classrooms. Fifty-two people were enrolled in the study. After applying planned exclusions, 50 participants remained for analysis. Sample size for the fidelity analysis used all those who responded to follow-up (49 of the 50 participants, for details see Figure 7). The sample size was determined based on prior work in which observational longitudinal physical activity data were used for theory and simulation refinement in system identification research (Freigoun et al., 2017; Hekler et al., 2016,

2018, King et al., 2013, 2016; Martin, Deshpande, Hekler, & Rivera, 2015). The sample ranges in age from 20 to 61 years ($M = 34.2$, $SD = 10.5$), and is comprised mostly of women (88%), non-students (68%), employed individuals (86%), and Minnesota residents (62%). Most of the sample identified as White (84%) or Asian (10%). All participants received a \$15 gift card for participating. Participants who completed the follow-up survey and responded to 80% or more of 24 surveys during the observation period received an additional \$10 gift card. This compensation schedule aligns with similar research (Wen, Schneider, Stone, & Spruijt-Metz, 2017), and results in an estimated hourly rate of \$8 to \$14.

1.14.3 Design

The study uses an intensive measurement longitudinal design (Rast et al., 2012).

1.14.4 Eligibility Criteria

Initial eligibility criteria. Several inclusion criteria were screened online. First, participants were English-speaking adults based in the U.S., 18-64 years of age, and physically capable of exercising enough to meet U.S. national guidelines (e.g., no prohibitive disabilities). Second, participants with occupations that “often” involved strenuous physical activity were ineligible⁵. Third, participants who participated in organized sports for physical activity (such as club soccer or intramural basketball) were ineligible. The screener highlighted that activities such as pick-up basketball, yoga or spin class, and casual running/cycling groups do not qualify as organized sports. The

⁵ For the first 172 people screened, those with occupations that “sometimes” involved strenuous physical activity were also ineligible. However, it became clear that this was too stringent as it resulted in the unintentional exclusion of people with occupations such as admin, customer service, and teacher. Thus, for the remaining 510 people who were screened, criteria were changed to only exclude those whose work “often” involved strenuous activity.

purpose of these criteria was to exclude athletes and those whose level of strenuous physical activity was high due to occupational necessities. Many studies of habitual and motivational processes in exercise take a similar approach (e.g., Kaushal et al., 2017; Philips & Gardner, 2016). Fourth, eligible participants were required to have a smart phone that could receive text messages and access the internet. Fifth, participants must have regularly used a qualifying Fitbit for at least two months prior to entry into the study. Qualifying Fitbits included all of those with heart-rate monitors available at the time of the study, such as Alta HR, Charge 1, 2, or 3 (with HR), Versa, Versa Lite, Ionic, Inspire HR, and Blaze. Participants must have also indicated that they regularly wore a Fitbit during exercise bouts such as running, swimming, biking, or weightlifting. Fitbits provide an estimate of one's *active minutes* and *active days* each week (details in the measures section below). Participants must have indicated that, within the last two months, they attempted to increase *active minutes* per week, and that they believed they had some success in making this change.

Verification of eligibility using Fitbit data. Increases in *active minutes* per week were verified by the research team using historical data on each participant's Fitbit. Historical data were defined as physical activity from eight weeks preceding the date on which participants shared access to their data. To qualify for the study, historical data must have met the following conditions. First, a positive linear increase (regardless of significance) was observed after fitting a regression line to the weekly total of active minutes for the first five weeks. Second, in none of the final three weeks did the participant's weekly active minutes fall below the lowest level of the first five weeks. Third, there was no more than one week in which the Fitbit was not worn for the whole

week. Days in which steps and number of calories burned from activity are equal to zero were considered non-wear days. The purpose of these criteria was to recruit people who were likely in the maintenance phase of behavior change. These participants successfully increased their physical activity over the course of several weeks, and either continued increasing or maintained the higher level of activity each subsequent week. Importantly, people did not qualify for the study if they had a lapse in their weekly activity level (i.e., a return to baseline or lower levels of activity) for three weeks since increasing their weekly active minutes. The purpose of these criteria was to exclude people who had already failed to maintain the initial increase in activity. See Figure 7 for a summary of eligibility criteria.

1.14.5 Procedure

1.14.5.1 Screening and Invitation to Enroll (Figure 7, T0a/b)

Participants were screened and invited to enroll in the study on a rolling basis. Recruitment materials were linked to an online screening survey that assessed an initial set of eligibility criteria (Figure 7, T0a). Those who met initial eligibility criteria received further information about the study and completed Consent to Access Data (Figure 7, T0b). Participants were then given step-by-step instructions on how to securely give the research team access to their Fitbit data. Participants were told that the research team would evaluate their data to ensure they met study criteria, and that they would be informed of their enrollment status within 5 business days. If the participants' data failed to meet criteria, they were informed via email, and thanked for their interest. If participants' data met criteria, they were invited to enroll in the study via email. The

invitation contained a link to complete an intake questionnaire. Technical support was made available via email.

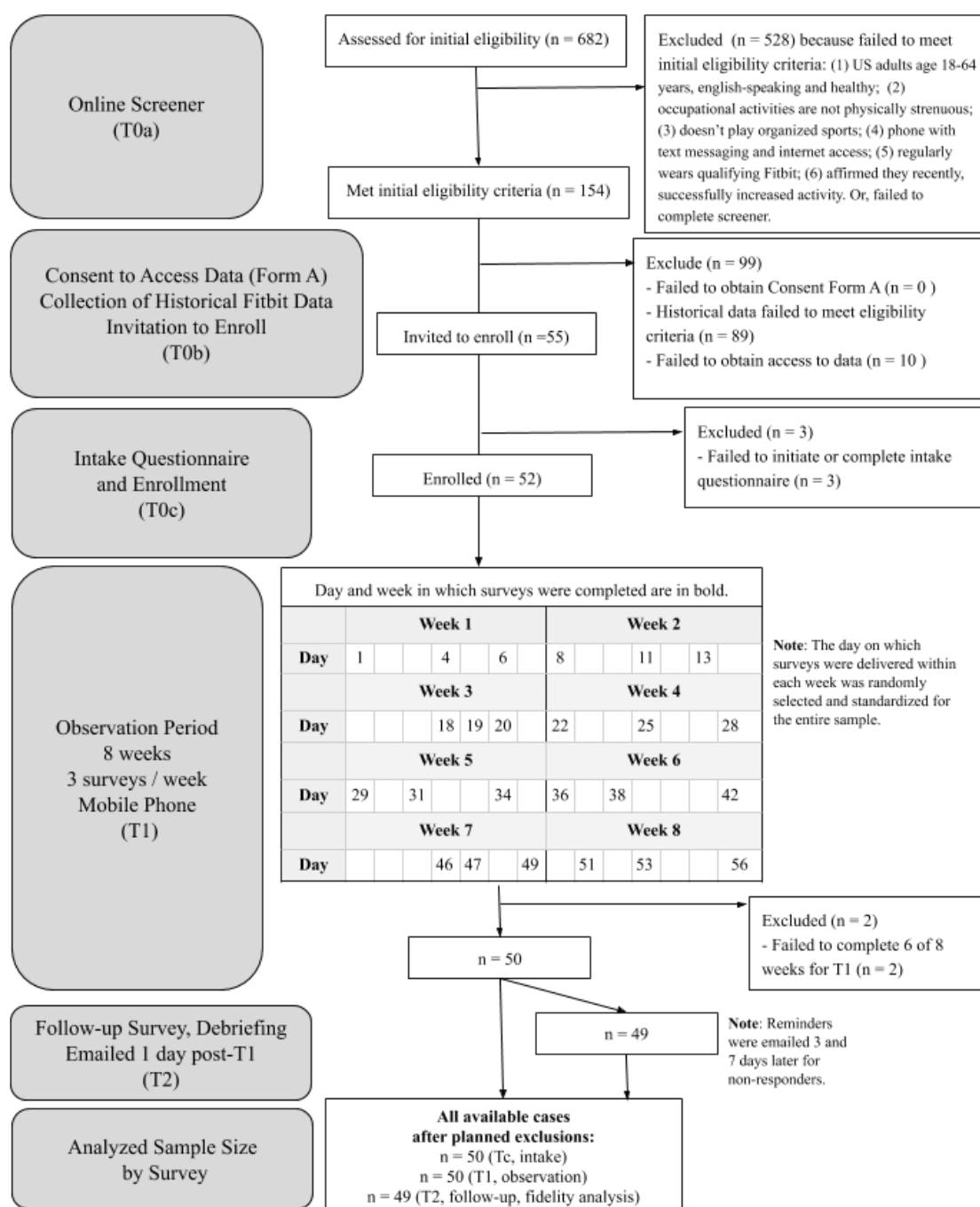


Figure 7. Study 2 CONSORT Diagram

1.14.5.2 Intake and Enrollment (Figure 7, T0c)

Participants completed an intake survey within five days of receiving the invitation. After three days, non-responders were reminded to complete the intake survey. The survey asked participants to complete Informed Consent (Form B), which again presented information from Consent Form A, but with a focus on the study moving forward. The survey covered demographics, described procedure, and defined terms used throughout the study. The survey also contained baseline measures of motivational and habitual processes.

After consent and responses to demographic questions were obtained, participants were told that “cardiovascular exercise is a physical activity that noticeably increases your heart rate for at least 10 minutes.” It was further explained that the researchers were interested in cardiovascular exercise that is done during “leisure time for recreation, or a workout, not work-related physical activity or scheduled organized sports,” and that participants can get this type of exercise in many ways, such as “running, biking, lifting weights, or very brisk walking.” Participants then selected different types of exercise they did on a regular basis from a list of 21 options (e.g., “Run/Jog,” “Exercise machine,” “Commute by bike,” and “Yoga”; Table 4), and reported whether they typically wear their Fitbit during those specific activities. Participants could also write in exercises that were not listed. Following these selections, participants were reminded that they “recently attempted to increase exercise” and that they were “successfully able to make this change.” They were then asked to think about their personal experience during bouts of exercise since they made this change, and to focus on how they felt “in-the-moment of exercising” while answering questions. These

instructions were followed by assessments of motivation for exercise (i.e., affect experience and satisfaction, see Measures Section). Following measures of motivation, instructions defined and gave examples of how one might *prepare* for exercise (i.e., instigation behaviors). Participants then wrote in and/or selected from a list of 7 types of preparatory tasks they typically did before exercising (e.g., “readying supplies, clothes, or equipment,” “scheduling,” “thinking about the best time, or how to make time, for exercise”). The purpose of this procedure was to help participants see the distinction between preparing to exercise (i.e., instigation) and engaging in the act of exercise (i.e., performance), which they were then told was a distinction of interest to the researchers. Following these instructions, participants answered questions measuring habitual processes (automaticity and context stability) separately for both instigation and performance of exercise.

Table 4. Types of exercise participants reported they do on a regular basis.

| n | % of sample | Type of exercise |
|----------|--------------------|-----------------------------------------------------------------------|
| 36 | 72% | Walk for exercise |
| 25 | 50% | Run/Jog |
| 24 | 48% | Exercise machine (ex: elliptical, Stairmaster) |
| 23 | 46% | Lift weights |
| 20 | 40% | Group fitness classes (ex: indoor cycling, yoga) |
| 12 | 24% | Yoga |
| 11 | 22% | Riding a bicycle |
| 7 | 14% | Circuit training |
| 6 | 12% | Other: spin bike, boxing, water aerobics, Pilates, lawn mowing, Zumba |
| 5 | 10% | Commute by other |
| 5 | 10% | Swim |
| 4 | 8% | Do calisthenics |
| 3 | 6% | Commute by bike |
| 1 | 2% | Rock climbing |
| 1 | 2% | Yoga |
| 1 | 2% | Basketball |
| 1 | 2% | Bowling |
| 1 | 2% | Volleyball |

Note: Participants could select all that were applicable and add their own under "Other:"

The intake survey concluded with instructions for registering participants' phones with SurveySignal (Hofmann & Patel, 2015), a text-messaging service used to deliver surveys during the observation period. Participants were also reminded of the procedure moving forward: They were asked to continue exercising as they normally would over the next two months, and they received an email with all pertinent instructions. Technical support was made available via email, and any issues (e.g., failure to register phone) that were not resolved within five days of receiving the invitation resulted in exclusion from the study (see Figure 7). Participants were enrolled in the observation period beginning the day after completing intake.

1.14.5.3 Observation Period (Figure 7, T1)

The observation period started the day following intake, and lasted for eight weeks (56 days). During this time, participants' physical exercise was passively tracked via Fitbit, and they responded to brief surveys delivered by text message. SurveySignal and Qualtrics were used in combination to deliver surveys at 7:00 PM (local time to participant) on three randomly selected evenings each week. Through piloting and expert consultation, it was determined that this sampling schedule would yield enough assessments to adequately measure the week-level motivational and habitual processes of interest, while also avoiding too many assessments that might burden the participants or feel overly repetitive. The randomly determined schedule by which participants receive surveys was fixed for the entire sample (see Figure 7). The surveys during this period covered measures of motivational and habitual processes. Additionally, two questions assessed whether the participant performed and/or instigated exercise that day. Specifically, participants were asked "Did you complete 10+ minutes of cardiovascular exercise today?" and "Did you prepare for today's exercise?" A brief example of what was meant by cardiovascular exercise and preparation (i.e., instigation) was presented alongside the question. The phrasing of subsequent questions assessing motivation and habitual processes was tailored to whether or not the participant performed and/or instigated exercise that day.

1.14.5.4 Follow-up (Figure 7, T2)

A follow-up survey was emailed after completion of the observation period. Non-responders received reminders via email three and seven days after the initial follow-up. The follow-up survey covered fidelity checks, technical issue reports, open-ended prompts regarding why participants may have failed or succeeded in maintaining the

increase in exercise, and the participant's intentions to exercise in the future. Participants were debriefed at the end of the questionnaire, and compensation was emailed to the participant within the week. If participants failed to respond to the follow-up survey, they were compensated after 14 days following the end of the observation period.

1.14.5.5 Collecting Fitbit Data

Participants enrolled in the study gave permission for researchers to access physical activity data from their Fitbit, which were downloaded to a secure server. Two months of historical data were downloaded to verify eligibility during the enrollment period (Figure 1, T0b). Once the study started, data were pulled monthly from all enrolled participants until the entire sample completed the observation period. Data were pulled for a final time for each participant as they completed observation. Physical activity data were the only data downloaded from participant's Fitbit (no other information in the account was used). Physical activity data from Fitbit included daily values for: the date, estimated calories burned, estimated calories burned from activity, steps, distance, and floors. Additionally, minutes spent in sedentary behavior, light activity, fairly active behavior, and very active behavior each day were included in the download.

1.15 Measures

Study 2 focused on three broad constructs—physical exercise, and motivational and habitual processes related to exercise—which are summarized in Table 5.

1.15.1 Physical Exercise

1.15.1.1 Active Minutes

Fitbit devices recognize activities that are more strenuous than regular walking. This includes everything from a brisk walk to weight training, a cardio workout, or a run. Fitbit's proprietary algorithm classified each wear-minute as sedentary activity, lightly active, fairly active, or very active. Active minutes were earned for activities at or above 3 metabolic equivalents (METs), which were classified as either "fairly" and "very" active minutes and used as a measure of time spent in moderate-to-vigorous physical exercise. Fitbits with HR monitoring more accurately classify active minutes for non-step-based activities, such as weight lifting, strenuous yoga, and rowing (Fitbit, n.d.). For these reasons, only participants who wore a Fitbit with HR monitoring were enrolled. Taking an approach similar to prior research (e.g., Ramirez, 2016) a measure of participants' weekly level of moderate-to-vigorous physical exercise (i.e., *weekly active minutes*) was estimated from Fitbit data. This was calculated by the summing of "fairly" and "very" active minutes for the seven days in each of the eight study-weeks.

1.15.2 Validity and Reliability of Fitbits for Measurement of Exercise

Fitbit has not publicly released information related to the accuracy of devices, although they are frequently used in health research, including dynamical systems research (e.g., Huberty et al., 2016; Freigoun et al., 2017). Nevertheless, a growing number of scientific studies examining validity and reliability of various Fitbit devices. A recent review of 22 studies found that several Fitbit step estimates were highly correlated ($r_s > .80$) with direct observation and validated measurement tools such as the Yamax CW-700 pedometer and Actigraph GT3X accelerometer (Evenson, Goto, & Furberg, 2015). However, this review was of older Fitbits, without HR monitoring (i.e., Fitbit Classic, Fitbit Ultra, Fitbit One, Fitbit Zip, and Fitbit Flex). There are fewer studies of

newer Fitbits with HR monitoring (i.e., Alta HR, Charge HR, Versa, and Ionic), and fewer still that also focus on energy expenditure or Fitbit's activity intensity categories (sedentary, lightly active, fairly active, very activity), which are pertinent to the present study. One study found that estimates of energy expenditure for the Charge HR were moderately correlated with standard assessments ($r = .53$; Li et al., 2018). Others have found similar correlations, and highlight that the Charge HR tends to underestimate energy expenditure and intensity, but that accuracy increases with exercise intensity (e.g., Jo & Dolezal, 2016). Despite inaccuracies, it appears that these early studies agree that the Fitbit Charge HR meets accepted standards of energy expenditure and intensity estimation—a mean absolute percent error less than 10% (Dondzila et al., 2018). To my knowledge all available studies of Fitbits with HR monitoring focus on an early version of the Charge HR, as opposed to newer devices (i.e. Charge 3 HR, Alta HR, Versa, and Icon). Furthermore, because the present study allows for different Fitbit devices, it is important to understand inter-device reliability. The only available review of the topic focuses on steps and expenditure of non-HR devices (i.e., Classic, Ultra, One, and Flex), but found consistently high inter-device correlations ($rs > .8$; Evenson et al., 2015).

1.1.1. **Type of Fitbit worn**

The number of participants by Fitbit device worn during the study was as follows: Charge 2 HR (15), Versa (11), Alta HR (9), Charge 3 HR (9), Blaze (4), Ionic (1), and Charge 1 HR (1).

Table 5. Summary of study 2 measures

| Variable | Source/Description | Historical Period | Intake (baseline) | Observation Period |
|----------------------------------------|-------------------------------------------------------------------------------------------------------|--------------------|-------------------|--------------------|
| Motivational Process | | | | |
| Affective Experience | | | | |
| 1 Affect | Adapted from BREQ-2-IR and MPAM-R-E | NA | 4-items | 4-items |
| Satisfaction with Experience | | | | |
| 2 Individual-Specific | Individually specific outcomes selected from mREI | NA | 3-items | 3-items |
| 3 Global Assessment | Adapted from Baldwin & Sala (2018) and Baldwin et al. (2009) | NA | 1-item | 1-item |
| Habitual Process | | | | |
| Automaticity | | | | |
| 4 Instigation | Adapted from SRBAI (Gardner et al., 2012; Phillips & Gardner, 2016; Gardner, Phillips, & Judah, 2016) | NA | 3-items | 3-items |
| 5 Performance | | NA | 3-items | 3-items |
| Context Stability | | | | |
| Instigation | | | | |
| 6 Specific | Adapted from Ji and Wood (2007) | NA | 3-items | 3-items |
| 7 Global | | NA | 1-item | NA |
| Performance | | | | |
| 8 Specific | Adapted from Ji and Wood (2007) | NA | 4-items | 4-items |
| 9 Global | | NA | 1-item | NA |
| Behavior | | | | |
| Moderate-to-Vigorous Physical Exercise | | | | |
| 10 Active Minutes | Sum of slightly and very active minutes | Passive Collection | NA | Passive Collection |

1.15.3 Motivational Constructs

1.15.3.1 *Affective Experience*

Four items were adapted from two scales to assess affective experience associated with physical exercise during intake and the observation period: (1) the Enjoyment/Interest Subscale of the Motives for Physical Activity Questionnaire-Revised (MPAM-R-E; Ryan et al., 1997), and (2) the Intrinsic Regulation Subscale of the Behavioral Regulation in Exercise Questionnaire-2 (BREQ-2-IR; Markland & Tobin, 2004; Mullan, Markland, & Ingledew, 1997). Scales were combined into a single measure, because they have strong convergent validity, and likely measure a common construct (Chmielewski et al., 2016).

At intake, participants were asked to think about their personal experience during a bout of exercise since initiating an increase in exercise. Participants were instructed to “focus on how you feel in-the-moment of exercising” while they answered these questions. The prompt, “When I am exercising...” was followed by four items (“I like the excitement of it,” “I enjoy it,” “It’s interesting,” and “It’s stimulating”), that were presented on a 4-point scale (1 = Strongly disagree; 2 = Disagree; 3 = Agree; 4 = Strongly agree). The mean of items was taken with higher scores representing more positive affective experiences.

During the observation period, participants were prompted three times each week. The four items and response options were the same as those used at intake, save modification of language to the past tense. On days that the participant exercised, items were preceded by the following prompt: “Reflect on the exercise you did today. To what extent do the following describe your experience during today’s exercise?” On days that

the participant did not exercise, items were preceded by “Reflect on the exercise you did in the recent past. To what extent do the following describe your experience during that exercise.” The question was also asked on non-exercise days to ensure that participants who exercised less did not have higher rates of missing data. The weekly mean of these items were used in analyses.

Deviations from source measures. In the interest of reducing participant burden and remaining conceptually coherent, five items from the original MPAM-R-E and BREQ-2-IR were not assessed. Two of the removed items—“I like to do this activity” (MPAM-R-E) and “I find exercise a pleasurable activity” (BREQ-2-IR)—were highly correlated ($r > .9$) with the “I enjoy it” item that was used, and thus likely redundant (see Chmielewski et al., 2016). Two items that were also removed—“It makes me happy” (MPAM-R-E), “satisfaction from participating” (BREQ-2-IR)—place more focus on an outcome of exercise rather than an experience during exercise, and thus overlap with the measurement of satisfaction that was used. Finally, one item, “I exercise because it’s fun” (BREQ-2-IR) was removed to reduce participant burden. Additionally, instructions were modified from original measures to focus on affective experiences *during a bout* of exercise, rather than *reasons why* people exercise. This measurement approach blends two theoretically distinct constructs—*affective judgments* that are affective experiences assessed reflectively (i.e., not during a bout of exercise) and *affective responses* that are assessed in-the-moment of exercising. This is a reasonable approach given that traditional use of MPAM-R and BREQ-2 at least partially captures in-the-moment affect (Rhodes et al., 2009). Most items, for example, “I enjoy my exercise sessions” and “It’s stimulating,” are clearly focused on affect during exercise despite not being assessed

during exercise. I took this approach because I am most interested in reflections on (or judgments of) in-the-moment affective experiences. Furthermore, given the study design, I cannot reasonably assess affect during a bout of exercise. Finally, it is worth noting that items used in my study are similar to those used in the popular Physical Activity Enjoyment Scale (PACES; Kendzierski & DeCarlo, 1991); for example, “I enjoy exercise” (for details see Appendix A).

1.15.3.2 Satisfaction with Experience

The most common assessment method for this construct—and the closest to its conceptual definition—is a single item, global assessment of perceived satisfaction, which has been used in several behavioral domains, including exercise (Baldwin & Sala, 2018; Baldwin et al., 2009). Following prior research, I also used a single item presented on a four-point scale (1 = Extremely dissatisfied; 2 = Somewhat dissatisfied; 3 = Somewhat satisfied; 4 = Extremely satisfied) to assess satisfaction with experience: “In general, how satisfied are you with what you have experienced *as a result* of increasing your cardiovascular exercise?” This item was assessed at intake. During the observation period, the item was modified to “How satisfied are you with what you have experienced as result of exercising today?” If the participant did not exercise that day, the question was reframed to focus on the “recent past.” The weekly mean was used for analysis of responses during the observation period.

In the exercise domain, multi-item assessments of satisfaction with specific outcomes are also common, for example, the Modified Reasons for Exercise Inventory (mREI; Cash, Now, & Grant, 1994; Chmielewski et al., 2016; Sears & Stanton, 2001). I adapted the mREI to assess satisfaction with outcomes pertaining to each participant’s

top three reasons for exercise, with a focus on the time since the participant increased their exercise. Specifically, at intake participants selected their top three reasons for exercising from a list of 14 possible reasons (e.g., lose weight, cope with stress/anxiety, and improve appearance; Table 6). If their most important reason(s) were missing from the list, participants entered their own. Participants were then asked, “How satisfied are you that your current level of exercise is achieving your goals or reasons for exercising?” The three individual-specific reasons were presented on a four-point scale (1 = Extremely dissatisfied; 2 = Somewhat dissatisfied; 3 = Somewhat satisfied; 4 = Extremely satisfied). During the observation period, the same prompt and three individual-specific reasons were presented three times per week. The weekly mean of items during the observation period was used for analyses.

Table 6. Participants’ top reasons for exercising

| n | % of sample | Reasons for exercising |
|----------|--------------------|-------------------------------------------------------------------|
| 33 | 66% | lose weight |
| 32 | 64% | improve overall health |
| 15 | 30% | improve appearance |
| 11 | 22% | improve strength |
| 10 | 20% | cope with stress-anxiety |
| 10 | 20% | improve mood |
| 10 | 20% | improve overall body shape |
| 5 | 10% | improve endurance-stamina |
| 5 | 10% | improve flexibility-coordination |
| 5 | 10% | maintain weight |
| 5 | 10% | increase energy level |
| 3 | 6% | have fun |
| 2 | 4% | cope with sadness-depression |
| 1 | 2% | meet new people |
| 1 | 2% | avoid chronic health conditions that I am predisposed to as I age |
| 1 | 2% | feelings of accomplishment |
| 1 | 2% | improve quality of sleep |

Note: Participants selected their top three reason and were able to add their own.

1.15.4 Habitual Constructs (for Instigation and Performance)

Each of the following measures of habitual processes was adapted to assess instigation and performance behaviors separately (Gardner, Phillips, & Judah, 2016). As described in detail above, instigation and performance were defined for participants in the intake survey instructions, examples were provided, and participants were asked to select examples specific to how they prepare for exercise. Following prior research (e.g., Gardner et al., 2016; Kaushal et al., 2017), the stem proceeding each measure distinguishes between *performance* (e.g., “Engaging in the act of exercise...”) and *instigation* (e.g., “Preparing for exercise...”) in a way that aligned with definitions and examples presented to participants at intake.

1.15.4.1 Context Stability

Questions adapted from Ji and Wood (2007) were used to measure context stability. At intake, one-item presented on a 4-point scale (1 = Strongly disagree; 2 = Somewhat disagree; 3 = Somewhat agree; 4 = Strongly agree) was used to assess global context stability. For example, the item for performance behavior reads: “When I engage in the act of exercise, I typically do it in a similar way each time” Additionally, four items assessed stability of exercise performance across four specific contexts (location, time of day, mood, and people involved). The item about “people involved” was excluded for the measure of stability of exercise instigation. An example of one item reads: “In general, each time I engage in the act of exercise ... the LOCATION in which I do it is...” displayed on a 4-point scale that reads: “1 = not at all similar to usual; 2 = somewhat similar to usual; 3 = very similar to usual; 4= exactly the same as usual.”

During the observation period, stability of the specific context was assessed with the same items and the same response scale as was done at intake. However, the prompt

focuses on the particular day or recent past depending on whether the participant exercised and/or planned to exercise that day. For example, the prompt for the measure of instigation either read “when I prepared for today’s exercise...” or “Recently, when I have prepared to exercise, it was something...” followed by the three specific contexts. The weekly mean of instigation and the weekly mean of performance were used in analyses.

1.15.4.2 Automaticity

The Self-Report Behavioral Automaticity Index (SRBAI; Gardner et al., 2012)—a subscale of the 12-item Self-Report Habit Index (SRHI; Verplanken & Orbell, 2003)—was used to assess automaticity of performance and instigation behaviors. The stem of each question distinguishes between performance (e.g., “Engaging in the act of exercise is something...”) and instigation (e.g., “Preparing for exercise is something...”). To reduce participant burden, three items, instead of the usual four, were selected for use: “I do without having to consciously remember”; “I do without thinking”; “I start doing before I realized I’m doing it.” Items were presented on a 4-point scale (1 = Strongly disagree; 2 = Somewhat disagree; 3 = Somewhat agree; 4 = Strongly agree).

Identical to the measurement approach for context stability, prompts were altered for the observation period to focus on that day or the recent past depending on whether the participant exercised and/or prepared for exercise on that particular day. For example, the prompt to measure automaticity of exercise performance either read, “Today’s exercise was something...” or “Recently, when I have exercised, it’s something...” and was followed by the three items. The weekly mean of instigation and the weekly mean of performance were used in analyses.

1.15.5 Reliability of Motivational Measures

Assessment of statistical reliability is presented in Table 7 of the results section and focuses on internal consistency, which varied across measures. A Cronbach's Alpha greater than or equal to .70, and an average inter-item correlation (AIC) between .15 and .50 were considered adequate levels of reliability following standard recommendations (Clark & Watson, 1995). Measures of affect, instigation automaticity, and performance automaticity met the Alpha criteria, but were above the recommended limit for AIC, suggesting substantial item redundancy (particularly for the two automaticity measures). Affect (AIC = .59) was also above the AIC threshold, however lower than prior estimates (AIC range = .72 to .82; Chmielewski et al., 2016), reflecting the approach of the present study to omit the most redundant items as per recommendations of Chmielewski and colleagues (2016). In contrast, measures of context stability for performance and instigation of exercise failed to meet the Alpha criteria, but were within the accepted range for AIC, which suggests that these measures included a broader range of content. Alpha and AIC could not be calculated for single-item measures (i.e., global satisfaction, performance context stability, and instigation context stability) and the measure of individually specific satisfaction (because the three items vary by person).

1.16 Results

Results are broken into several sections. The first section addresses how a technical malfunction in the delivery of surveys was handled in analyses, and discusses planned exclusion. The second section explores the question: Are participants in a maintenance phase of behavior change as intended? With this objective in mind, historical data were used to compare activity levels of participants in the study to those

who were ineligible. The pattern of means for motivational and habitual variables just prior to enrollment is then assessed with an eye toward theoretical predictions. In the third section, attention is turned to trends during the observational period: Were participants able to maintain increases in exercise? The section begins with a discussion of missing data, which is determined to be inconsequential for results. Descriptive statistics for motivation and habit variables during the observational period, and physical exercise during historical and observational periods are then presented. The section concludes with observations on overall trends, and potential implications for theories of sustained behavior change. The fourth section explores the following question: (1) When motivation and habit variables are higher than person-specific or sample means in a given week, are participants more active? And, how do motivation and habit variables relate to each other over time? In this section, the modeling approach is described and results are presented. In the fifth and final section of results, two questions are explored: (1) Is it possible to distinguish successful and unsuccessful maintainers based on activity data? (2) How do the trajectories of motivational and habitual variables differ between those who maintained increases in exercise and those who did not?

1.16.1 Results Part 1: Accounting for a Malfunction and Planned

Exclusions

1.16.1.1 Accounting for a Technical Malfunction

The text messaging service used to deliver surveys during the observation period malfunctioned, resulting in the sampling schedule shifting forward one day for all assessments on or following April 12, 2019. After applying planned exclusion (see

below), 33 participants were affected by the malfunction.⁶ The number of days affected varies by participant because recruitment was rolling. To address the issue, I maintained the 56-day observation period as planned; however, participants affected by the malfunction received 2 or 4 surveys in some weeks (instead of the planned 3 surveys per week, see Table 8). As planned, the mean of assessments was aggregated to the week for analyses. Additionally, affected participants received the final survey on study-day 57, outside the planned observation window. This final assessment was removed from all analyses, and thus analyses rely upon 23 assessments for affected participants instead of the planned 24. All of the results that follow take this approach unless otherwise specified.

1.16.1.2 Planned Exclusions

Participants must have responded to surveys during the observation period at least once per week for at least 6 of the 8 weeks to be included in analyses. Only 2 participants failed to meet the criteria, and were removed from all of the following analyses.⁷

1.16.2 Results Part 2: Are participants in a maintenance phase of change?

Participants who had recently increased physical exercise were recruited. Historical data from Fitbits was used to determine whether participants had initial success in maintaining this increase, with the goal of recruiting a sample in the maintenance

⁶ Three participants who were within the malfunction window were not affected for reasons unknown. The text messaging service (SurveySignal) never replied to emails regarding the malfunction. Before applying exclusions, 34 participants were affected by the malfunction.

⁷ Before applying the fix to the SurveySignal malfunction one participant (instead of two) met the exclusion criteria, results are unaffected.

phase of behavior change (Rothman, 2000). This section presents evidence that participants are in a maintenance phase of change as intended.

1.16.2.1 Exercise among ineligible and eligible participants: An analysis of activity prior to enrollment

Eight weeks of historical activity data from participants' Fitbits were assessed for eligibility prior to enrollment in the study. I obtained and assessed historical data from 144 people, among whom 89 were ineligible and 55 were eligible. Among eligible people, 3 failed to complete intake and thus 52 were enrolled in the study. Among those enrolled, 2 participants met planned exclusion criteria (see Figure 7 for details). For the following analysis, the 50 participants who completed the study are compared to 89 who were ineligible.

Historical activity data were assessed to determine whether participants were in a maintenance phase of behavior change. This was defined as a positive regression slope in activity over the first five weeks, and activity levels in the subsequent three weeks that remained above the lowest activity level in the first five weeks. As depicted in Figure 8, weekly mean activity minutes among people who were ineligible and those who were enrolled clearly differed in the intended fashion: Those who were enrolled initiated and maintained an increase in physical exercise. The observed differences are robust to removal of participants who were ineligible as a result of having more than one whole week in which they failed to wear their Fitbit (20 of the 89 ineligible participants), and inclusion of those who were enrolled but met planned exclusion criteria (2 of 52 enrolled participants).

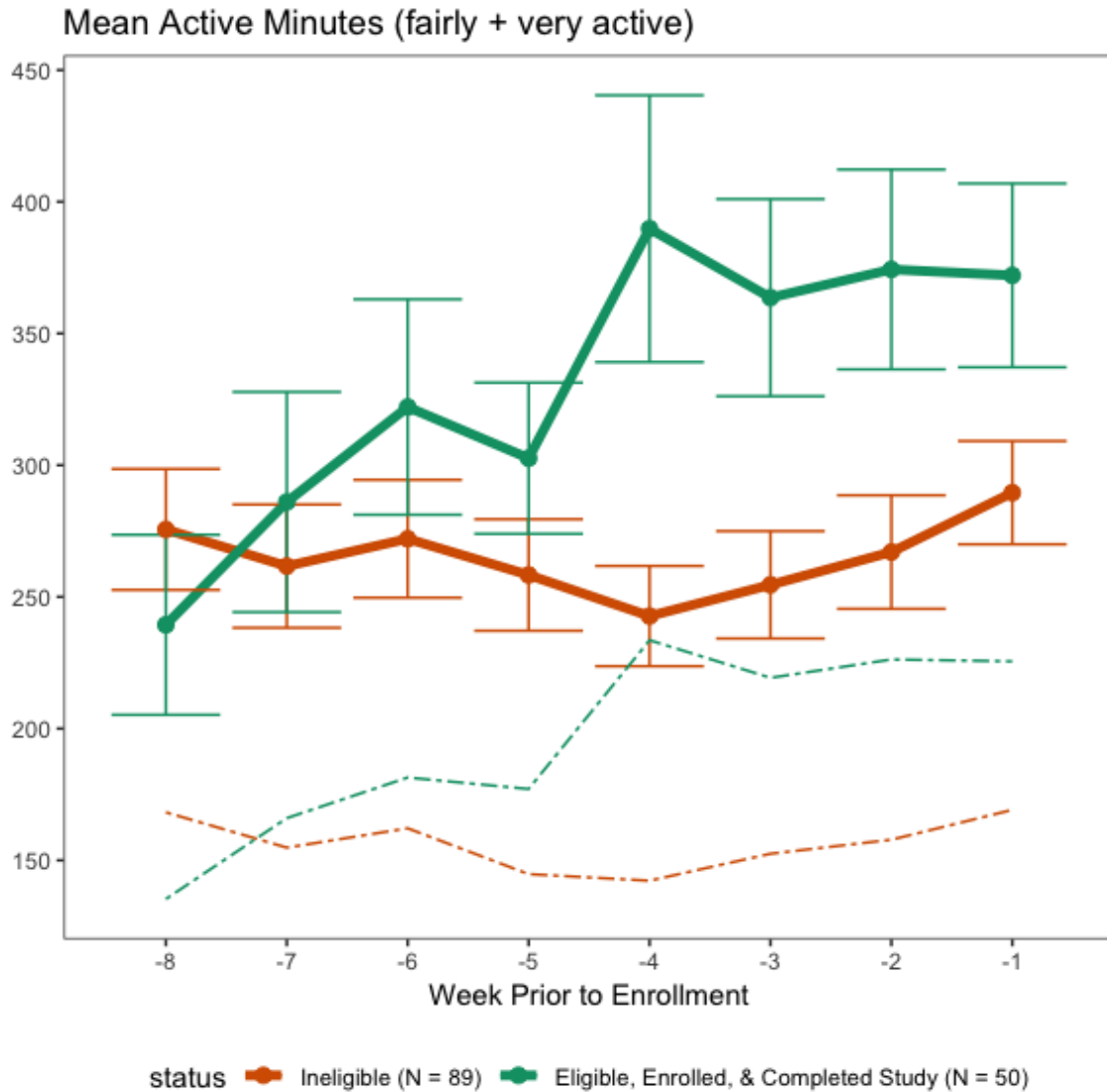


Figure 8. Comparison of active minutes for ineligible and enrolled participants during the 8 weeks prior to enrollment in the study.

Note: Solid lines are mean weekly total of fairly and very active minutes with standard error depicted. Dashed lines are weekly mean level of very active minutes only. Weeks -8 through -1 are on the x-axis, which represent the historical period and precedes the observation period.

Linear mixed effects models indicate that there was a statistically significant positive increase in activity minutes over the first five weeks among enrolled participants ($b = 31.90, t = 5.74$), and that this positive slope significantly differed from that of ineligible participants ($b = 39.70, t = 6.47$). Over the first five weeks, the average slope among eligible participants was 32.0 (SD = 24.0, Q1 = 16.4, Median = 25.9, Q3 = 44.4, n

= 50). In contrast, the average slope among ineligible participants was -9.89 (SD = 64.9, Q1 = -23.0, Median = -5.5, Q3 = 6.8, n = 83)⁸. Additionally, as can be seen in Figure 8, the two groups had similar levels of activity during the first few weeks, and enrolled participants achieved a higher activity level by the fifth week, which was maintained for the subsequent three weeks (M = 370.0, SD = 243.7, n = 50) compared to ineligible participants (M = 264.0, SD = 157.7, n = 87). Additional descriptive statistics and missingness for enrolled participants' activity are presented in Tables 8, 9, and 10.

1.16.2.2 Profile of Motivation and Habit Variables at Intake

Descriptive statistics for all nine psychological measures administered at intake are presented in Table 7. There are three measures of motivation (affective, specific satisfaction, and global satisfaction), and six measures of habit (automaticity, specific context stability, and global context stability for exercise instigation and performance respectively). All measures were assessed on the same response scale.

Potential implications for theories of sustained change. The intake assessments of motivational and habitual variables were assessed soon after participants increased their level of exercise, and demonstrated that they were able to maintain the increase for three weeks. Thus, the sample was explicitly recruited based on a behavioral profile that plausibly reflects people who are in a maintenance phase of change. The observed psychological profile of the sample at intake also indicates that participants are in a maintenance phase (see Figure 9). In other words, mean levels of motivational variables are high, and meaningfully higher than mean levels of habit variables, which are closer to

⁸ Six ineligible participants had too little data to calculate a slope. Each participant's slope was calculated using linear regression (as per eligibility requirements). Some ineligible participant had a positive slope but failed to meet other eligibility criteria.

the middle of the scale. This aligns with expectations regarding baseline levels of these constructs, which are depicted in the hypothetical scenarios of Figure 6 of the hypotheses section. In particular, affect and satisfaction are significantly higher than automaticity and specific context stability of instigation and performance (paired t -tests, all p 's < .0001 save associations between specific satisfaction and stability instigation ($p = .004$), and performance ($p = .079$, Figure 9). The exception to this pattern was the measure of global context stability, which was at similar mean levels to the motivation variables.

Furthermore, some variables within the motivation construct differed from one another, whereas others did not. Specifically, within-person levels of affect and global satisfaction did not differ from each other ($p = .679$), but were both statistically higher than that of specific satisfaction (paired t -tests, $p = .047$ and $p = .001$, respectively). The theoretical implication of the observed pattern within motivation constructs is unclear and there is dearth of guidance from the literature. It was expected that motivation variables would be high at baseline, but given the novelty of measuring satisfaction that is specific to each person's reasons for exercising it is unclear why it might be lower. One possibility is that in the absence of specific information on which to judge satisfaction, people over-emphasize the prevailing valence. In contrast, when specific reasons for exercise are judged, lack of satisfaction become more apparent. Perhaps the specific assessment of satisfaction is a more sensitive measure. Finally, levels of positive affect were also higher than specific satisfaction, which may indicate that increases in affect precede increases in satisfaction, perhaps during initiation of behavior change. Additional data are needed to draw more definitive conclusions.

Similarly, there were differences among the habit constructs. Specifically, context

stability of performance and instigation did not differ ($p = .132$), but were significantly higher than automaticity of performance ($p = .008$ and $p = .036$ respectively) and instigation ($p = .011$ and $p = .048$ respectively), which also did not differ from each other ($p = .883$). This may indicate that increases in context stability precede increases in automaticity, which aligns well with the theoretical rationale behind these measures. For example, the relation behind measures of context stability is that automaticity (or habit formation) increases as the behavior is more frequently paired with consistent context. However, some have argued, and the present data seem to support the idea that context stability does not imply automaticity (Gardner, 2015). Furthermore, based on the present results, theorizing that has emphasized the distinction between habitual instigation and performance (e.g., Phillips & Gardner, 2016) may lack an empirical standing—at least in how these constructs are typically operationalized. The similarity between measures of habitual instigation and performance fails to provide evidence aligning with Hypothesis 4 and Hypothetical Scenarios B, C, F, and G of Figure 6.

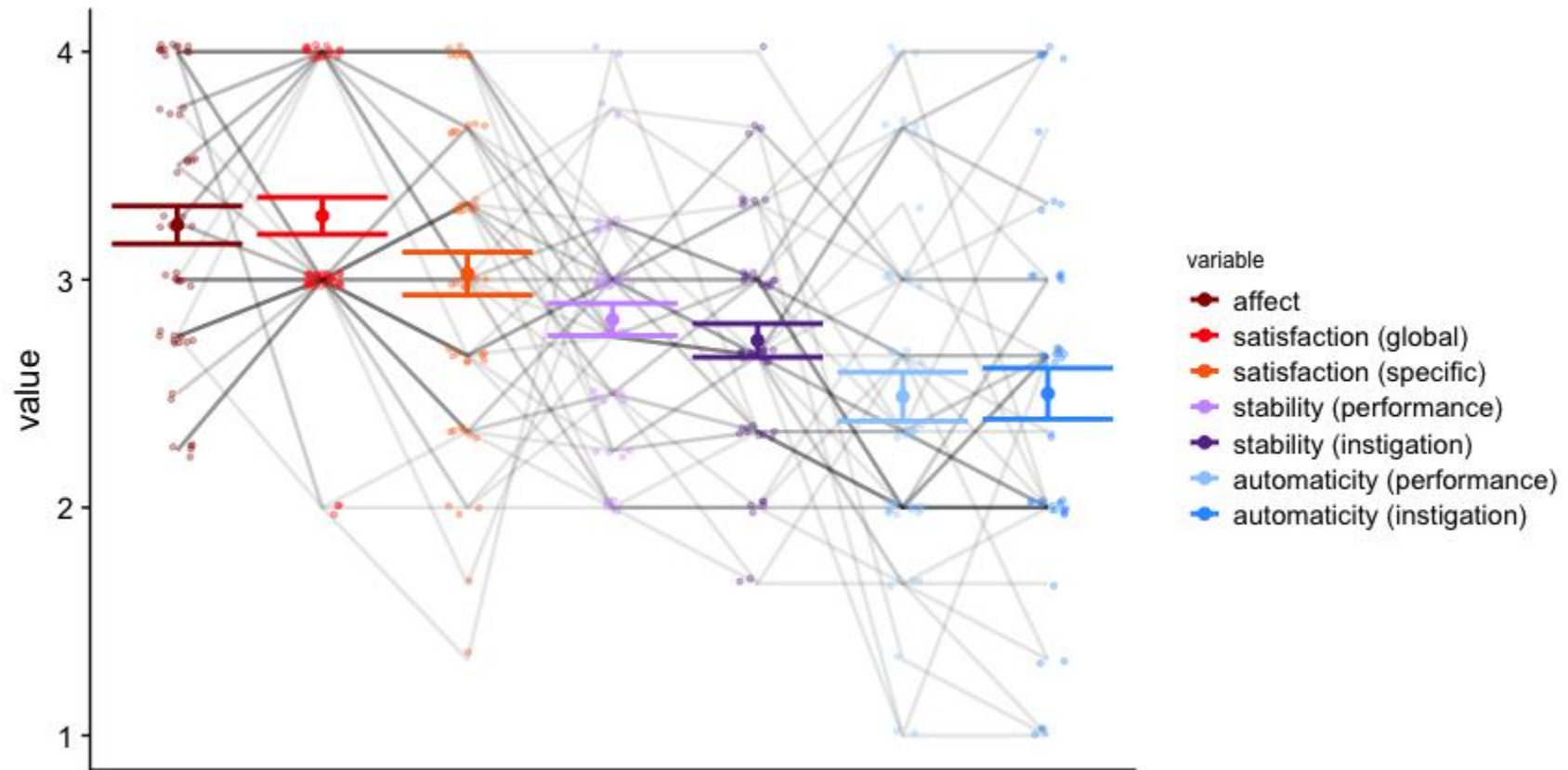


Figure 9. Motivation and habit variables at intake reflect predictions that the sample is in a maintenance phase at this time

Note: Mean and standard error are plotted with motivational variables in hot colors, and habit variables in cool colors. Each participant's score is plotted (faint colored points). Gray lines represent each participant ($n = 50$). Within-person differences across variables can be visualized from gray trajectories. Darker gray lines represent more common within-person trends. Indicative of the maintenance phase, motivational variables tend to be higher than habit variables between- and within-person.

Table 7. Descriptive statistics and correlation matrix for all measures at intake (baseline) are presented.

| variables | | n | M | SD | Med | Min | Max | Skew | Kurt. | α_s | AIC | Pearson Correlation Matrix | | | | | | | |
|-------------------|---------------------|----|------|------|------|------|-----|-------|-------|------------|------|----------------------------|------|-------|------|------|------|------|------|
| | | | | | | | | | | | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Affective | | | | | | | | | | | | | | | | | | | |
| 1 | Affect | 50 | 3.24 | 0.59 | 3.25 | 2.25 | 4 | -0.09 | -1.27 | 0.85 | 0.59 | | | | | | | | |
| Satisfaction | | | | | | | | | | | | | | | | | | | |
| 2 | Individual-Specific | 50 | 3.03 | 0.67 | 3 | 1.33 | 4 | -0.32 | -0.58 | NA | NA | 0.31 | | | | | | | |
| 3 | Global Assessment | 50 | 3.28 | 0.57 | 3 | 2 | 4 | -0.06 | -0.62 | NA | NA | 0.31 | 0.66 | | | | | | |
| Automaticity | | | | | | | | | | | | | | | | | | | |
| 4 | Instigation | 50 | 2.50 | 0.79 | 2.67 | 1 | 4 | 0.21 | -0.49 | 0.89 | 0.73 | 0.27 | 0.42 | 0.4 | | | | | |
| 5 | Performance | 50 | 2.49 | 0.76 | 2.33 | 1 | 4 | 0.37 | -0.57 | 0.87 | 0.70 | 0.34 | 0.49 | 0.48 | 0.66 | | | | |
| Context Stability | | | | | | | | | | | | | | | | | | | |
| Instigation | | | | | | | | | | | | | | | | | | | |
| 6 | Specific | 50 | 2.73 | 0.52 | 2.67 | 1.66 | 4 | 0.11 | -0.35 | 0.44 | 0.20 | 0.11 | 0.35 | 0.3 | 0.29 | 0.25 | | | |
| 7 | Global | 50 | 3.38 | 0.67 | 3 | 2 | 4 | -0.58 | -0.76 | NA | NA | -0.07 | 0.04 | -0.07 | 0.16 | 0 | 0.34 | | |
| Performance | | | | | | | | | | | | | | | | | | | |
| 8 | Specific | 50 | 2.83 | 0.50 | 3 | 2 | 4 | 0.18 | -0.20 | 0.57 | 0.25 | 0.09 | 0.09 | 0 | 0.15 | 0.11 | 0.66 | 0.08 | |
| 9 | Global | 50 | 3.18 | 0.69 | 3 | 1 | 4 | -0.60 | 0.47 | NA | NA | -0.07 | 0.26 | 0.23 | 0.02 | 0.18 | 0.42 | 0.34 | 0.39 |

Note: All variables were presented on a 4-point scale.

1.16.3 Results Part 3: Were participants able to maintain increases in exercise? What are the overall trends in motivation and habit variables?

This section begins with a discussion of missing data and response rate, which were favorable and thus inconsequential for analyses. Attention is then turned to activity, motivation, and habit during the observation period. Descriptive statistics during the observation period are presented, and overall trends are interpreted in reference to predictions from theories of sustained behavior change.

1.16.3.1 Missing Data and Response Rate

Survey Data. The number of missing responses per week for survey data during the observational period was low (Table 8). Zero participants failed to respond to at least one survey per week for the first four weeks, and attrition over time was minimal (i.e., only 1, 2, or 3 participants missing data for weeks 5-8). A conservative approach to calculating response rate, which includes all 24 assessments for all participants (even those affected by the malfunction), reveals a mean response rate of 90.0%. Twenty participants responded to all surveys, twenty-three responded to 20-23 surveys, and seven responded to fewer than 20 surveys. When participants responded to surveys, the completion rate was also high. Forty-three participants completed 100% of surveys they responded to, four completed 95-99%, and the remaining three completed 84-93%.

Table 8. Survey Response Rate During the Observational Period

| Sample size for 0, 1, 2, 3, and 4 responses/week to delivered surveys | | | | | | | % of sample responding to 3+ surveys |
|--------------------------------------------------------------------------|---|---|---------|---------|---------|---------|--------------------------------------------|
| | 0 | 1 | 2 | 3 | 4 | | |
| Week | 1 | 0 | 1 | 1 | 48 (50) | NA | 96% |
| | 2 | 0 | 2 | 7 | 41 (50) | NA | 82% |
| | 3 | 0 | 5 | 7 | 38 (50) | NA | 76% |
| | 4 | 0 | 6 | 29 (32) | 15 (18) | NA | 30% |
| | 5 | 1 | 2 | 3 | 27 (18) | 17 (32) | 88% |
| | 6 | 1 | 9 | 27 (33) | 13 (17) | NA | 26% |
| | 7 | 2 | 1 | 9 | 38 (50) | NA | 76% |
| | 8 | 3 | 1 | 9 | 37 (50) | NA | 74% |
| | 9 | 3 | 30 (33) | NA | NA | NA | |

Note: Due to survey delivery malfunction, the number of participants for which 1, 2, 3, or 4 assessments were delivered is presented in parentheses. For example, in Week 5, three assessments were delivered to 18 participants, and four assessments were delivered to 32 participants. The assessment delivered in the ninth week due to malfunction is presented in grey and was removed from all analyses.

Fitbit Activity Data. The number of participants who failed to wear their Fitbit on 0, 1 ..., or 7 days each week is presented in Table 9. Missing Fitbit data are infrequent: Most participants had zero non-wear days for all study-weeks. Further, there appears to be no attrition. Sample size for interim-days—the number of days that it took participants to complete intake, register phone, and enroll in observation after completion of the historical period—is also presented in Table 9. Activity data during this time are excluded from analyses. Most participants had only one or two interim-days.

Table 9. Missing Data: Fitbit Non-Wear Days

| week | non-wear days | | | | | | | |
|----------------------------------------------------|----------------------|----------|----------|----------|----------|----------|----------|----------|
| <i>Historical period prior to study enrollment</i> | | | | | | | | |
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| -8 | 39 | - | 6 | 1 | 1 | 2 | 1 | - |
| -7 | 45 | 2 | - | 1 | - | 1 | - | 1 |
| -6 | 45 | 1 | 1 | 1 | 1 | - | - | 1 |
| -5 | 44 | 1 | 3 | - | 2 | - | - | - |
| -4 | 46 | 2 | - | 1 | 1 | - | - | - |
| -3 | 44 | 5 | - | 1 | - | - | - | - |
| -2 | 45 | 2 | 3 | - | - | - | - | - |
| -1 | 47 | 1 | 1 | - | - | 1 | - | - |
| <i>Days between historical and observational*</i> | | | | | | | | |
| | - | 13 | 26 | 2 | 5 | 3 | 0 | 1 |
| <i>Observational period</i> | | | | | | | | |
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | 47 | 1 | - | 1 | - | 1 | - | - |
| 2 | 47 | 3 | - | - | - | - | - | - |
| 3 | 47 | 2 | 1 | - | - | - | - | - |
| 4 | 47 | 3 | - | - | - | - | - | - |
| 5 | 47 | 1 | 1 | - | - | - | 1 | - |
| 6 | 44 | 4 | 2 | - | - | - | - | - |
| 7 | 50 | - | - | - | - | - | - | - |
| 8 | 45 | 3 | 2 | - | - | - | - | - |

Note: Missingness presented as number of participants (n = 50) who failed to wear Fitbit for 0, 1, 2,..., or 7 days for each week. *Sample size for number of days it took to complete intake, register phone, and enroll in observational period after completion of the historical period. Activity during this time is not analyzed.

1.16.3.2 Changes in exercise during historical and observational period

Each participants' active minutes during the historical and observational period are plotted in Figure 10, descriptive statistics for which are in Table 10. In what follows, I make several observations based on visual inspection of these data. There was considerable between-person variability in average weekly activity minutes. For example, during the historical period, weekly activity ranged from 11 to 1,435 minutes with a mean of 370 and a standard deviation of 250 (see "overall mean" of historical period in Table 10). Despite the variability, most participants started the historical period below recommended activity levels (USDHHS, 2018). Specifically, the median participant had 157 active minutes in Week -8, and 235 active minutes over the first five week of the historical period (i.e., the initiation phase of behavior change). Furthermore, by the end of the historical period, most participants increased activity to meet recommended levels. The median participant averaged 331 active minutes for the last three weeks of the historical period (i.e., the early maintenance phase of change).

Most participants also met recommended activity levels during the observation period (i.e., the maintenance phase of change, Median = 295 minutes). Average activity minutes appears slightly lower during observation ($M = 351$; $SD = 211$; Median = 295) than during last three weeks of the historical period ($M = 270$; $SD = 244$; Median = 331), indicating that some people successfully maintained initial increases in activity and some did not. Figure 10 reveals these trends. In particular it appears that participants who had a more dramatic increase in activity during the historical period were less able to maintain the increase during observation (e.g., the heavy exerciser who exceeds 2,000 minutes one

week, see upper-left plot of Figure 10). In contrast, participants who started at medium levels of activity (see the second row of plots from the bottom in Figure 10) and made modest increases in the historical period, appear to be most successful in maintaining those increases. Furthermore, this group appears to have had less week-to-week variability in active minutes (see the right plot in second row from bottom of Figure 10, and compare it to other plots on right-hand side). However, conclusions from visual inspection are limited by the plot's scale. Differences among people who successfully and unsuccessfully maintained increases will be explored in greater detail in later sections (i.e., Results Part 5).

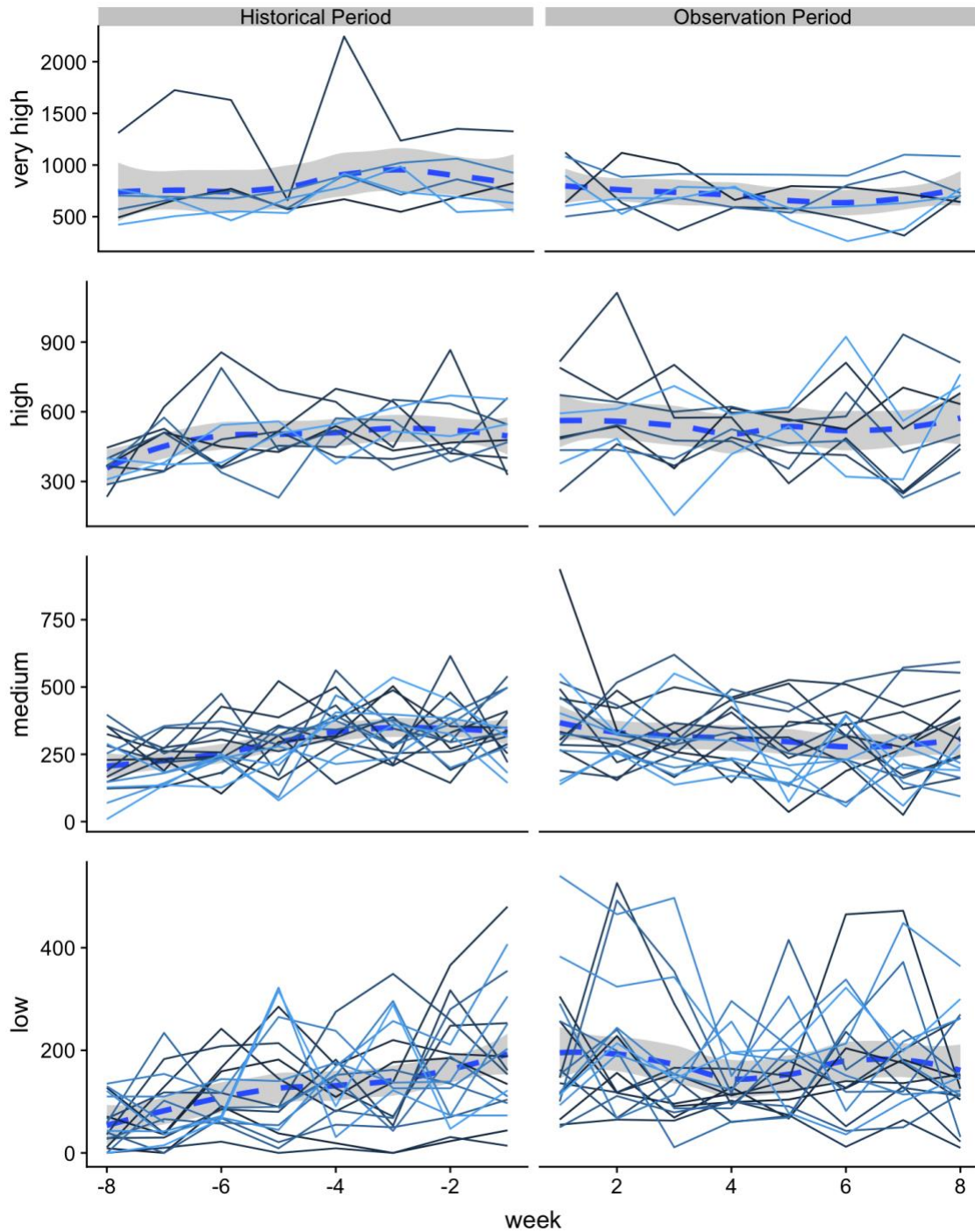


Figure 10. Changes in Activity Level for All Participants Throughout the Study

Note: Each participant ($n = 50$) is depicted in a different shade of blue, and their weekly active minutes are plotted for the historical and observation period. Dashed lines and shaded area represent the local polynomial regression fit (LOESS). To aid visual interpretation, plots are broken into four rows by level of overall mean active minutes during the historical period: low (< 200 min., $n=18$), medium (≥ 200 and < 400 min., $n=17$), high (≥ 400 and < 600 min., $n=9$), and very high (≥ 600 min., $n=6$).

Table 10. Descriptive Statistics for Weekly Active Minutes

| Week | n | Mean | SD | Min | Q1 | Median | Q3 | Max | Skew |
|------------------------------------------------------------------------------------|----------|-------------|-----------|------------|-----------|---------------|-----------|------------|-------------|
| <i>Historical Period</i> | | | | | | | | | |
| -8 | 50 | 239 | 242 | 0 | 65 | 157 | 360 | 1310 | 1.99 |
| -7 | 49 | 286 | 293 | 0 | 110 | 221 | 373 | 1725 | 2.52 |
| -6 | 49 | 322 | 286 | 22 | 117 | 243 | 427 | 1629 | 2.18 |
| -5 | 50 | 303 | 203 | 0 | 141 | 286 | 450 | 753 | 0.39 |
| -4 | 50 | 390 | 358 | 9 | 156 | 330 | 516 | 2245 | 2.84 |
| -3 | 50 | 364 | 265 | 0 | 185 | 321 | 499 | 1236 | 1.14 |
| -2 | 50 | 374 | 268 | 23 | 192 | 328 | 463 | 1351 | 1.37 |
| -1 | 50 | 372 | 247 | 14 | 192 | 334 | 494 | 1326 | 1.35 |
| <i>Mean for first five weeks of historical period (initiation of change)</i> | | | | | | | | | |
| | 50 | 307 | 259 | 8 | 127 | 235 | 430 | 1513 | 2.14 |
| <i>Mean for last three weeks of historical period (early in maintenance phase)</i> | | | | | | | | | |
| | 50 | 370 | 244 | 15 | 202 | 331 | 469 | 1304 | 1.45 |
| <i>Overall mean (across weeks of historical period)</i> | | | | | | | | | |
| | 50 | 331 | 250 | 11 | 165 | 275 | 453 | 1435 | 1.90 |
| <i>Observational Period</i> | | | | | | | | | |
| 1 | 50 | 389 | 268 | 50 | 155 | 316 | 515 | 1122 | 0.94 |
| 2 | 50 | 384 | 242 | 65 | 216 | 325 | 524 | 1118 | 1.09 |
| 3 | 50 | 344 | 241 | 11 | 153 | 292 | 492 | 1008 | 0.89 |
| 4 | 50 | 346 | 221 | 60 | 147 | 306 | 492 | 910 | 0.52 |
| 5 | 50 | 316 | 208 | 36 | 142 | 258 | 464 | 906 | 0.68 |
| 6 | 50 | 345 | 234 | 12 | 169 | 319 | 477 | 923 | 0.75 |
| 7 | 50 | 327 | 242 | 25 | 164 | 252 | 426 | 1100 | 1.31 |
| 8 | 50 | 362 | 253 | 10 | 150 | 294 | 540 | 1084 | 0.70 |
| <i>Overall mean (across weeks of observational period)</i> | | | | | | | | | |
| | 50 | 351 | 211 | 55 | 189 | 295 | 486 | 972 | 0.83 |

Note: Descriptive statistics are rounded to nearest integer. Active minutes are the sum of “fairly” and “very” active minutes readouts from each participant's Fitbit, and are earned for activities at or above 3 metabolic equivalents. The measure is often used as an estimate of time spent in moderate-to-vigorous physical exercise.

1.16.3.3 Motivation and habit during observation: Overall trends

Mean changes in motivation and habit variables over the eight-week observation period are plotted in Figure 11. In what follows, I make observations based on visual inspection of overall trends. First, mean levels across variables appear to differ in a

fashion similar to baseline: Motivational variables are generally higher than habitual variables, although there is a slight convergence over time. In particular, global satisfaction steadily decreases over the eight weeks of observation (light red line of Figure 11; linear mixed-effects model with random intercept and slope: $\beta = -.035$, $p < .0001$), whereas all other variables remained at roughly the same level throughout observation (all p 's $> .05$). However, some trajectories were non-linear. For example, automaticity of performance (light blue) and instigation (dark blue) follow nearly identical quadratic trajectories (with performance at slightly lower levels throughout); both increased over the first four weeks and then steadily declined over the last four weeks. In contrast, stability of performance and instigation followed slightly different trajectories from each other. Stability of performance increased over the first three weeks and declined over the remaining five (light purple), whereas stability of instigation remained at a similar level throughout (dark purple). Furthermore, stability of performance and instigation appear to meaningfully diverge by Week 8 (i.e., non-overlapping error bars), a pattern that aligns with expectations regarding one hypothetical scenario of successful maintenance (Hypothesis 4, Figure 6B). However, the pattern provides weak evidence, because it is subtle (only different in the final week) and these overall trends do not consider whether participants succeed or failed to maintain increases exercise.

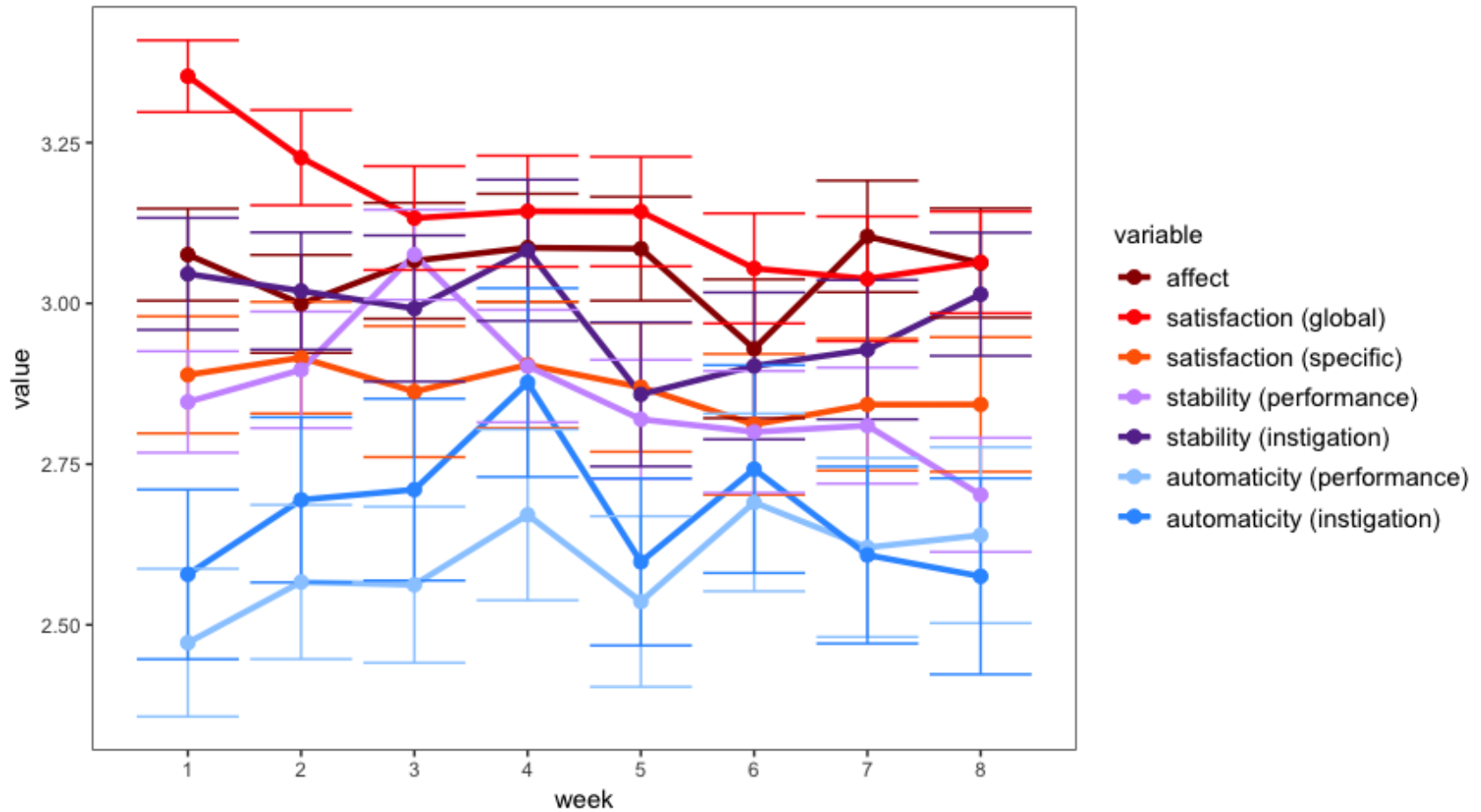


Figure 11. Changes in motivation and habit over time

Note: Solid lines are weekly mean total for each variable with standard error depicted. All variables were assessed on a 4-point response scale. Motivational variables are depicted in hot colors, whereas habit variables are depicted in cool colors.

1.16.4 Results Part 4: When motivation and habit variables are higher than person-specific or sample means in a given week, are participants more active? How do motivation and habit variables relate to each other over time?

In what follows, I explore two analytic approaches to estimating the relation between exercise, motivation, and habit over time, and whether successful maintainers have a different pattern of psychological trajectories than unsuccessful ones. First, the modeling approach is described and then results are presented.

1.16.4.1 Modeling Approach: Exploratory Mixed-Effects Analysis

The following analysis follows an approach used in prior observational research on longitudinal relations between physical activity and psychological constructs (e.g., Kowalski et al., 2018). Multilevel (i.e., mixed-effects) models are used to examine associations between changes in motivation and habit variables, and changes in physical exercise. The model allows for simultaneous assessment of the effects of within-person (level 1) and between-person (level 2) variation in predictor variables. In other words, the model helps to answer the following question: On weeks during which people's level of motivation/habitation is higher than their own mean (within-person) or higher than the sample's grand mean (between-person), are they more active? The models also examine the average individual change across the eight weeks of measurement (fixed slope effects) and whether trajectories of change varied across individuals (random slope coefficients). Models were fit using the lmer function in the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2017). These models assume that the error

structure is independent and normal, and that random effects are multivariate normal. The lme function in the nlme package (Pinheiro, Bates, DebRoy Sarkar, and R Core Team, 2016) was used to test model assumptions, which were determined to meet standards. All models were fit using Maximum Likelihood Estimation.

First, intercept-only models (dependent measures and no predictors) were fit to determine whether sufficient variance existed at level 1 and level 2 for each of the motivational and habitual measures to conduct the multilevel analyses:

Level 1:

$$Exercise_{ij} = \beta_{0i} + e_{ij}$$

Level 2:

$$\beta_{0i} = \gamma_{00} + U_{0i}$$

Second, I examined time-varying covariation models to determine whether changes in each motivation and habit variable (i.e., affective experience, satisfaction with experience, context stability, and automaticity) are associated with weekly exercise. These models included an index of time (starting at 0; Hoffman & Stawski, 2009). Level 1 estimates for motivational and habitual processes were person-mean centered (PMC). PMC is the value of the variable each week (PW) minus the individual's mean value across all weeks (PM). Thus, level 1 parameter estimates represent the effect of variation around each individual's own mean level motivation or habituation on active minutes (i.e., within-person effect). The level 2 parameter estimates represent the effect of between-person differences in motivation or habituation on active minutes (i.e., a between-person or person-mean (PM) effect).

Level 1:

$$\text{Active Minutes}_{ij} = \beta_{0i} + \beta_{1i}(\text{Week}) + \beta_{2i}(\text{PMC Predictor}) + e_{ij}$$

Level 2:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(\text{PM predictor}) + U_{0i}$$

$$\beta_{1i} = \gamma_{10} + U_{1i}$$

$$\beta_{2i} = \gamma_{20} + U_{2i}$$

The equations are specified such that active minutes on any given week will depend upon the number of weeks that have passed since starting the study (β_{1i}), the effect of within-person changes in motivational and habitual processes (β_{2i}), and person-specific residuals (e_{ij}). The γ_{00} intercept represents mean activity at baseline when all other predictor variables are zero. The γ_{01} estimate represents the pure between-person effect of motivational or habitual predictors on level of physical exercise. The γ_{10} slope parameter reflects rate of linear change in activity minutes across weeks, independent of the effect of within-person changes in motivational or habitual processes, and person-mean motivation or habit. In contrast, the γ_{20} slope parameter assesses whether higher (or lower) motivation or habit at a given week is associated with higher (or lower) activity minutes, independent of the effect of time and PM motivation or habit. This parameter, γ_{20} , is person-mean centered and represents the pure within-person effect of motivational or habitual processes, unconfounded by between-person sources of variance.

The same modeling approach was used to explore associations between motivation and habit variables over time. These models were used to test Hypothesis 2 and 3a of Figure 6 and were fit using the same process as above, except habitual variables served as the outcome and motivational variables as the predictor.

1.16.4.2 Modeling Results: Active Minutes and Psychological Variables

Intercept-only and baseline models. Examination of the “empty” model allowing only a random intercept showed substantial between-person variance in activity minutes (73.4%), leaving an additional 26.6% variance due to within-person or other unmeasured factors. Fitting a “baseline” longitudinal model by adding a random slope (i.e., adding time in weeks, and allowing it to vary) also indicated substantial between-person variance (76.6%), again indicating that most of the variability in weekly activity minutes was due to between-person differences, but also leaving enough variability to explore how within-person factors may relate to activity levels. This baseline longitudinal model with random intercept and slope was also significantly different from, and fit these data better than, the same model with slope fixed ($\chi^2(2) = 8.47, p = .014$). Thus, the baseline model with random intercept and slope was used in subsequent models in which motivation and habit predictors were added.

Account for malfunction. First, I explore the possibility that participants affected by the malfunction in survey delivery (as described above) differ from those who were not affected. Adding this dummy coded variable (1 = affected) as a fixed predictor to the baseline model revealed no significant difference between groups ($\beta = -59.4, 95\% CI = [-180.4, 61.5]$). Thus, modeling proceeded under the assumption that the malfunction does not affect results.

Changes across time. Time was included as a predictor in all models. All models showed slight linear declines in active minutes over the eight-week observation period, only one of which was significant (the model with automaticity of performance; Table 11). In general, variance in slope was low.

Within- and between-person associations. A significant positive within-person association was found between weekly activity minutes and automaticity of performance ($\beta = 91.7$, 95% $CI = [14.3, 169.1]$). On weeks during which automaticity of exercise performance was higher than the person's average automaticity across weeks, the person exercised for longer. Estimates for all other within-person association were negligible, in addition to all between-person associations (Table 11).

Fidelity check. Following the analysis plan, I explored the possibility that participants who went on vacation, left town, or moved during the study ($n = 25$), or those who were injured, sick, or ill such that it affected their ability to exercise during the study ($n = 23$), differed in their level of exercise. Dummy coded variables for “vacation” and “sick” with “1” representing an affirmative response were added as interaction terms with time to the baseline model. None of the estimates were significant (all p 's $> .05$), indicating that participants who were sick or on vacation did not differ in overall activity minutes or change in activity minutes over time compared to those who were not sick or did not vacation. Illness and vacationing likely occurred at random across the sample (e.g., heavy exercisers were no more likely to fall ill than were lighter exercisers). Thus, no additional fidelity issues were explored.

Table 11. Linear mixed effects models predicting weekly active minutes from motivation and habit variables

| Fixed Effects | | | | | | Random Effects | Model Fit | |
|----------------------------------------------------------------------------|-----------|-------|------|-----------------|----------|----------------|-----------|-------------|
| | | b | se | 95% CI | p-value | | var | AIC BIC |
| Intercept-only model: lme4::lmer(active.min ~ 1 + (1 id) ...) | | | | | | | | 5,148 5,160 |
| n = 50 | Intercept | 351.5 | 29.5 | [293.6, 409.3] | 0.0000** | Intercept | 41,644 | |
| obvs = 400 | | | | | | Residual | 16,739 | |
| Baseline model: lme4::lmer(active.min ~ 1 + week + (1 + week id)) | | | | | | | | 5,140 5,164 |
| n = 50 | Intercept | 372.5 | 31.7 | [310.3, 434.7] | 0.0000** | Intercept | 44,766 | |
| obvs = 400 | Slope | -6.0 | 3.4 | [-12.6, 0.6] | 0.0764 | Slope | 255 | |
| | | | | | | Residual | 13,384 | |
| Affect | | | | | | | | 5,041 5,073 |
| n = 50 | Intercept | 372.9 | 32.0 | [310.2, 435.6] | 0.0000** | Intercept | 45,648 | |
| obvs = 392 | Slope | -6.2 | 3.5 | [-13.1, 0.7] | 0.0794 | Slope | 300 | |
| | BP | 12.2 | 61.9 | [-109.1, 133.5] | 0.4877 | Residual | 13,119 | |
| | WP | -3.2 | 64.1 | [-128.9, 122.4] | 0.6126 | | | |
| Satisfaction (individually specific) | | | | | | | | 5,038 5,069 |
| n = 50 | Intercept | 371.5 | 31.3 | [310.2, 432.8] | 0.0000** | Intercept | 43,319 | |
| obvs = 392 | Slope | -6.0 | 3.5 | [-13, 0.9] | 0.0885 | Slope | 300 | |
| | BP | 75.0 | 44.4 | [-12, 162] | 0.0910 | Residual | 13,100 | |
| | WP | -52.7 | 51.5 | [-153.6, 48.3] | 0.3067 | | | |
| Satisfaction (global assessment) | | | | | | | | 5,034 5,065 |
| n = 50 | Intercept | 366.1 | 31.7 | [304, 428.1] | 0.0000** | Intercept | 44,332 | |
| obvs = 392 | Slope | -4.4 | 3.6 | [-11.4, 2.5] | 0.2117 | Slope | 284 | |
| | BP | 79.5 | 59.8 | [-37.7, 196.7] | 0.1836 | Residual | 12,948 | |
| | WP | -30.0 | 63.3 | [-154.1, 94.1] | 0.6356 | | | |
| Automaticity: Instigation | | | | | | | | 4,292 4,322 |
| n = 50 | Intercept | 382.4 | 31.6 | [320.5, 444.3] | 0.0000** | Intercept | 43,452 | |
| obvs = 332 | Slope | -6.5 | 3.9 | [-14.3, 1.2] | 0.0986 | Slope | 381 | |
| | BP | -3.7 | 35.0 | [-72.3, 65] | 0.9164 | Residual | 13,100 | |
| | WP | 42.7 | 39.1 | [-33.9, 119.3] | 0.2743 | | | |
| Automaticity: Performance | | | | | | | | 5,018 5,050 |
| n = 50 | Intercept | 380.4 | 32.3 | [317, 443.7] | 0.0000** | Intercept | 46,905 | |
| obvs = 392 | Slope | -8.3 | 3.5 | [-15.1, -1.5] | 0.0171** | Slope | 288 | |
| | BP | -17.5 | 36.3 | [-88.6, 53.6] | 0.6298 | Residual | 12,277 | |
| | WP | 91.7 | 39.5 | [14.3, 169.1] | 0.0202* | | | |
| Context Stability (specific): Instigation | | | | | | | | 4,295 4,325 |
| n = 50 | Intercept | 381.2 | 31.6 | [319.4, 443] | 0.0000* | Intercept | 43,271 | |
| obvs = 332 | Slope | -6.1 | 4.0 | [-13.9, 1.7] | 0.1266 | Slope | 388 | |
| | BP | 50.2 | 54.3 | [-56.3, 156.8] | 0.3552 | Residual | 14,273 | |
| | WP | -32.5 | 57.1 | [-144.4, 79.3] | 0.5683 | | | |
| Context Stability (specific): Performance | | | | | | | | 5,041 5,072 |
| n = 50 | Intercept | 372.8 | 31.9 | [310.2, 435.4] | 0.0000** | Intercept | 45,337 | |
| obvs = 392 | Slope | -6.2 | 3.5 | [-13.2, 0.7] | 0.0774 | Slope | 290 | |
| | BP | 44.6 | 60.8 | [-74.6, 163.8] | 0.4630 | Residual | 13,162 | |
| | WP | -47.6 | 63.0 | [-171.2, 75.9] | 0.4496 | | | |

Note: * $p < .05$; ** $p < .01$

1.16.4.3 Modeling Results: Associations between motivation and habit

Several models were fit to test Hypothesis 2 and 3a, results of which are presented in Tables 12a, 12b, and 12c. Hypothesis 2 states that motivational processes positively affect habitual processes, particularly instigation, and Hypothesis 3a states that habitual processes in performance undermine motivational processes. In these linear mixed effects models, habitual variables are regressed on motivational variables following the same approach above.

Changes across time. Time was included as a predictor in all models. None of the models showed linear changes in habit variables over the eight-week observation period (Table 12a-c). In general, variance in slope was very low, indicating that for most participants, habit variables did not change much over time.

Between-person associations. A significant positive between-person association was found between affect and all four habitual variables (automaticity of instigation and performance, and context stability of instigation and performance; Table 12a). All between-person associations for global satisfaction and the habit variables were also positive and significant (Table 12c). Similarly, all between-person associations for specific satisfaction were positive and significant except for performance stability. In sum, these results indicate that people more motivated than the sample average were also more likely to exercise habitually.

Within-person associations. A significant negative within-person association was found between weekly affect and automaticity of instigation ($\beta = -.57$, 95% $CI = [-1.01, -.13]$) and performance ($\beta = -.66$, 95% $CI = [-1.06, -.25]$; Table 12a). Additionally, a significant negative within-person association was found between weekly specific

satisfaction and automaticity of performance ($\beta = -.39$, 95% $CI = [-.72, -.06]$; Table 12b). Finally, a significant negative within-person association was found between weekly global satisfaction and automaticity of instigation ($\beta = -.70$, 95% $CI = [-1.12, -.27]$) and performance ($\beta = -.57$, 95% $CI = [-.97, -.18]$), and context stability of instigation ($\beta = -.34$, 95% $CI = [-.64, -.05]$; Table 12c). Taken together, on weeks in which motivation variables were lower than the person's average for that variable, automaticity (and in some cases stability) tended to be higher that week for that person. These results provide initial partial support for Hypothesis 3a: Within-person increases in automaticity of performance were associated with decreases in motivation. In other words, on weeks in which automaticity was higher, motivation was lower. However, Hypothesis 3a was not fully supported. This effect was also present for instigation automaticity (which was not expected from Hypothesis 3a), and the direction of the effect cannot be determined from these data (i.e., causal inferences are limited). Finally, these results provide initial evidence against Hypothesis 2, because no positive within-person association between motivation and habit variables were found.

Table 12a. Affect as Predictor of Habitual Variables (Linear Mixed Effects Models)

| Fixed Effects | | | | | | Random Effects | Model Fit | |
|-------------------------------------------------|------------------|-------|------|----------------|----------|------------------|-----------|---------|
| | | b | se | 95% CI | p-value | | var | AIC BIC |
| Predictor: Affect | | | | | | | | |
| Outcome: Automaticity (Instigation) | | | | | | | 507 | 538 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.62 | 0.11 | [2.41, 2.83] | 0.0000** | <i>Intercept</i> | 0.48 | |
| obvs = 332 | <i>Slope</i> | 0.00 | 0.01 | [-0.02, 0.02] | 0.9019 | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.77 | 0.22 | [0.35, 1.2] | 0.0004** | <i>Residual</i> | 0.16 | |
| | <i>WP</i> | -0.57 | 0.23 | [-1.01, -0.13] | 0.0117* | | | |
| Outcome: Automaticity (Performance) | | | | | | | 563 | 595 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.51 | 0.10 | [2.32, 2.7] | 0.0000* | <i>Intercept</i> | 0.40 | |
| obvs = 392 | <i>Slope</i> | 0.03 | 0.01 | [0, 0.05] | 0.0306* | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.88 | 0.20 | [0.49, 1.27] | 0.0000** | <i>Residual</i> | 0.14 | |
| | <i>WP</i> | -0.66 | 0.21 | [-1.06, -0.25] | 0.0014** | | | |
| Outcome: Context Stability (Instigation) | | | | | | | 476 | 506 |
| <i>n</i> = 50 | <i>Intercept</i> | 3.01 | 0.08 | [2.87, 3.16] | 0.0000** | <i>Intercept</i> | 0.20 | |
| obvs = 332 | <i>Slope</i> | -0.01 | 0.01 | [-0.03, 0.01] | 0.3001 | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.50 | 0.14 | [0.22, 0.78] | 0.0005** | <i>Residual</i> | 0.16 | |
| | <i>WP</i> | -0.30 | 0.15 | [-0.6, 0] | 0.0523 | | | |
| Outcome: Context Stability (Performance) | | | | | | | 513 | 545 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.95 | 0.07 | [2.81, 3.09] | 0.0000** | <i>Intercept</i> | 0.00 | |
| obvs = 392 | <i>Slope</i> | -0.03 | 0.01 | [-0.05, 0] | 0.0393* | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.31 | 0.13 | [0.04, 0.57] | 0.0225* | <i>Residual</i> | 0.00 | |
| | <i>WP</i> | -0.18 | 0.14 | [-0.46, 0.11] | 0.2199 | | | |

Note: * $p < .05$; ** $p < .01$

Table 12b. Satisfaction (Individually Specific) as Predictor of Habitual Variables (Linear Mixed Effects Models)

| Fixed Effects | | | | | | Random Effects | Model Fit | |
|--------------------------------------------------------|------------------|-------|------|----------------|----------|------------------|-----------|---------|
| | | b | se | 95% CI | p-value | | var | AIC BIC |
| Predictor: Satisfaction (Individually Specific) | | | | | | | | |
| Outcome: Automaticity (Instigation) | | | | | | | | 499 530 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.61 | 0.10 | [2.41, 2.8] | 0.0000** | <i>Intercept</i> | 0.43 | |
| obvs = 332 | <i>Slope</i> | 0.01 | 0.01 | [-0.01, 0.02] | 0.5877 | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.68 | 0.15 | [0.38, 0.97] | 0.0000** | <i>Residual</i> | 0.16 | |
| | <i>WP</i> | -0.31 | 0.18 | [-0.66, 0.04] | 0.0848 | | | |
| Outcome: Automaticity (Performance) | | | | | | | | 571 602 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.50 | 0.10 | [2.32, 2.69] | 0.0000** | <i>Intercept</i> | 0.40 | |
| obvs = 392 | <i>Slope</i> | 0.03 | 0.01 | [0, 0.06] | 0.0219 | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.65 | 0.15 | [0.36, 0.93] | 0.0000** | <i>Residual</i> | 0.14 | |
| | <i>WP</i> | -0.39 | 0.17 | [-0.72, -0.06] | 0.0218* | | | |
| Outcome: Context Stability (Instigation) | | | | | | | | 473 503 |
| <i>n</i> = 50 | <i>Intercept</i> | 3.00 | 0.07 | [2.86, 3.14] | 0.0000** | <i>Intercept</i> | 0.19 | |
| obvs = 332 | <i>Slope</i> | -0.01 | 0.01 | [-0.03, 0.01] | 0.4580 | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.43 | 0.10 | [0.23, 0.63] | 0.0000** | <i>Residual</i> | 0.16 | |
| | <i>WP</i> | -0.13 | 0.14 | [-0.41, 0.15] | 0.3586 | | | |
| Outcome: Context Stability (Performance) | | | | | | | | 508 540 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.94 | 0.07 | [2.8, 3.09] | 0.0000** | <i>Intercept</i> | 0.21 | |
| obvs = 392 | <i>Slope</i> | -0.02 | 0.01 | [-0.05, 0] | 0.0467* | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.19 | 0.10 | [-0.01, 0.39] | 0.0564 | <i>Residual</i> | 0.14 | |
| | <i>WP</i> | 0.11 | 0.13 | [-0.15, 0.36] | 0.4142 | | | |

Note: * $p < .05$; ** $p < .01$

**Table 12c. Satisfaction (Global Assessment) as Predictor of Habitual Variables
(Linear Mixed Effects Models)**

| Fixed Effects | | | | | | Random Effects | Model Fit | |
|----------------------------------------------------|------------------|-------|------|----------------|----------|-------------------|--------------|---------|
| | | b | se | 95% CI | p-value | | var | AIC BIC |
| Predictor: Satisfaction (Global Assessment) | | | | | | | | |
| Outcome: Automaticity (Instigation) | | | | | | | 513 | 543 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.60 | 0.10 | [2.4, 2.8] | 0.0000** | <i>Intercept</i> | 0.44 | |
| obvs = 332 | <i>Slope</i> | 0.01 | 0.01 | [-0.01, 0.03] | 0.4511 | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.83 | 0.21 | [0.43, 1.24] | 0.0001** | <i>Residual</i> | 0.17 | |
| | <i>WP</i> | -0.70 | 0.22 | [-1.12, -0.27] | 0.0013** | | | |
| Outcome: Automaticity (Performance) | | | | | | | 562 | 594 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.47 | 0.09 | [2.29, 2.66] | 0.0000** | <i>Intercept</i> | 0.39 | |
| obvs = 392 | <i>Slope</i> | 0.04 | 0.01 | [0.01, 0.06] | 0.0035** | <i>Slope</i> | 0.01 | |
| | <i>BP</i> | 0.87 | 0.19 | [0.49, 1.25] | 0.0000** | <i>Residual</i> | 0.14 | |
| | <i>WP</i> | -0.57 | 0.20 | [-0.97, -0.18] | 0.0045** | | | |
| Outcome: Context Stability (Instigation) | | | | | | | 471 | 501 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.98 | 0.07 | [2.83, 3.12] | 0.0000** | <i>Intercept</i> | 0.18 | |
| obvs = 332 | <i>Slope</i> | 0.00 | 0.01 | [-0.02, 0.02] | 0.8823 | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.59 | 0.13 | [0.33, 0.85] | 0.0000** | <i>Residual</i> | 0.16 | |
| | <i>WP</i> | -0.34 | 0.15 | [-0.64, -0.05] | 0.0234* | | | |
| Outcome: Context Stability (Performance) | | | | | | | 517 | 548 |
| <i>n</i> = 50 | <i>Intercept</i> | 2.94 | 0.07 | [2.8, 3.08] | 0.0000** | <i>Intercept</i> | 0.20 | |
| obvs = 392 | <i>Slope</i> | -0.02 | 0.01 | [-0.05, 0] | 0.0692 | <i>Slope</i> | 0.00 | |
| | <i>BP</i> | 0.33 | 0.13 | [0.07, 0.58] | 0.0124* | <i>Residual</i> | 0.14 | |
| | <i>WP</i> | -0.26 | 0.15 | [-0.55, 0.03] | 0.0737 | | | |

Note: * $p < .05$; ** $p < .01$

1.16.5 Results Part 5: How do the trajectories of motivation and habit variables differ between successful and unsuccessful maintainers?

In this final section of results, I first attempt to define and identify participants who successfully (and unsuccessfully) maintained increases in exercise. Second, I descriptively present and interpret differences in the trajectories of motivation and habit variables between those who maintained increases in activity and those who failed to do so.

1.16.5.1 Exploratory Latent Class Analysis

The preregistration for this analysis described that, in an exploratory fashion, latent class mixed (LCM) models would be fit to activity data, with the goal of identifying two or three classes of trajectories. It was expected that this approach might reveal trajectories indicative of maintenance, non-maintenance, and possibly growth. Under the assumption that these empirically derived classes adequately distinguished between maintainers and non-maintainers, the plan was to descriptively explore differences between classes in the trajectories of motivation and habit variables. Two classes emerged from this modeling approach; however, upon visual inspection none of the models revealed classes as expected. The different classes that emerged primarily described overall differences in activity (i.e., people who, on average, were very active versus people who were less active), as opposed to differences in trajectories (i.e., successful versus unsuccessful maintenance). This result makes sense given the large between-person variability in overall activity levels and low variability in slopes discussed in previous sections. In the following section, I describe the LCM models that were fit and present results from one exemplary model before dropping this approach. I

then conduct an exploratory analysis in which I define successful and unsuccessful maintainers, and descriptively interpret differences between these groups in the trajectory of motivation and habit variables.

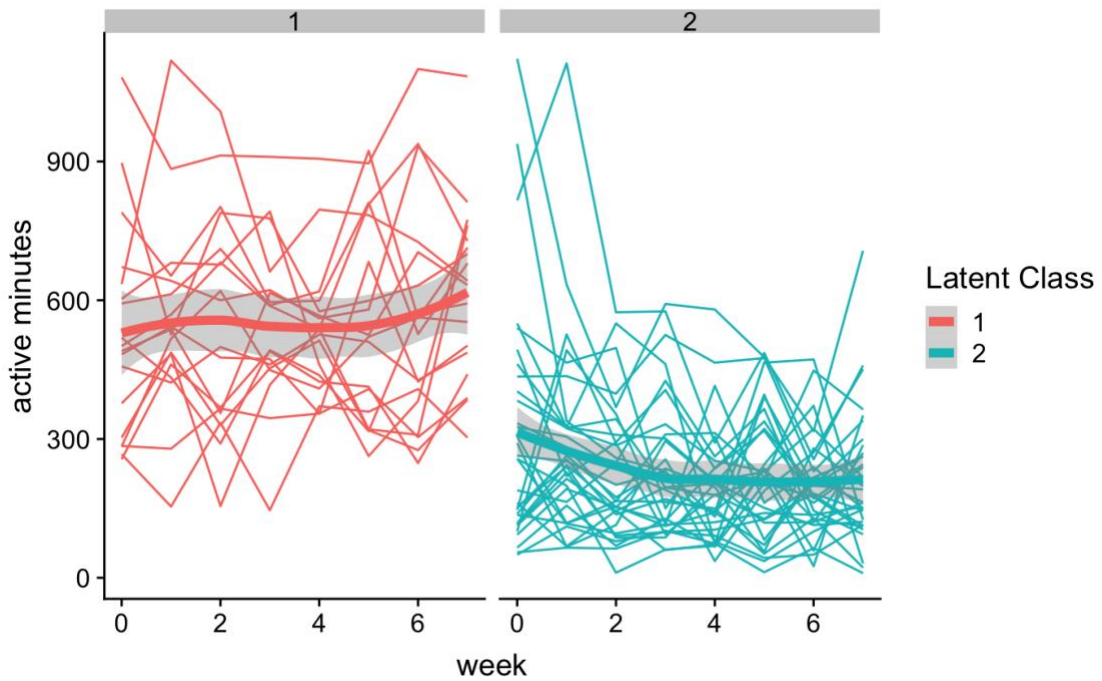
Latent class mixed models were fit using the `lcmm` package in R (Proust-Lima et al., 2018). As was done for prior modeling, the time variable (week) started at zero. I explored which of five function fitting types—linear, quadratic, or splines with 2, 3, or 4 nodes located at quantiles of the marker distribution—best fit activity data during observation for each of two or three latent classes. For example, the quadratic LCM equation for two classes took the following form in R:

```
lcmm(active.min ~ poly(week, degree = 2, raw = TRUE),
      random = ~ poly(week, degree = 2, raw = TRUE),
      mixture = ~ poly(week, degree = 2, raw = TRUE),
      ng = 2,
      subject = "id",
      link = "beta",
      data = data_obv_pa_wk)
```

Results from this analysis are presented in Table 13. Models with three classes failed to have a large enough sample within each class for further consideration. As described above, among the models with two classes and adequate fit, the classes primarily differed in overall level of activity. The best fitting of these models, the quadratic one, is presented in Figure 10. As can be seen, class one and two largely differ by overall level of activity, which is not relevant to the present study. All other models have the same result; thus, this analysis approach was abandoned.

Table 13. Summary of Latent Class Mixed Models Explored

| Function Type | # of classes | loglik | npm | BIC | %class1 | %class2 | %class3 |
|---------------|--------------|---------|-----|--------|---------|---------|---------|
| Linear | 2 | -2564.1 | 9 | 5163.4 | 8 | 92 | na |
| Quadratic | 2 | -2506.3 | 16 | 5075.3 | 36 | 64 | na |
| Splines 2Q | 2 | -2511.3 | 14 | 5077.3 | 30 | 70 | na |
| Splines 3Q | 2 | -2516.7 | 12 | 5080.4 | 20 | 80 | na |
| Splines 4Q | 2 | -2516.1 | 13 | 5083.0 | 20 | 80 | na |
| Linear | 3 | -2553.3 | 12 | 5153.5 | 8 | 28 | 64 |
| Quadratic | 3 | -2497.4 | 20 | 5073.0 | 8 | 28 | 64 |
| Splines 2Q | 3 | -2508.9 | 17 | 5084.3 | 30 | 6 | 64 |
| Splines 3Q | 3 | -2512.6 | 15 | 5084.0 | 6 | 30 | 64 |
| Splines 4Q | 3 | -2511.9 | 16 | 5086.4 | 6 | 30 | 64 |

**Figure 12. Individual Trajectories for Active Minutes by Latent Classes from the Quadratic Model**

1.16.5.2 *Defining successful and unsuccessful maintenance*

Successful maintainers were defined as participants whose mean weekly active minutes during the 8-week observation period was higher than their mean weekly active minutes during the three weeks prior to entry in observation (i.e., the last three weeks of the historical period). These three weeks were selected for comparison because they mark the beginning of the maintenance phase, and align with the rationale behind the eligibility criteria. To qualify for the study, participants had to increase activity levels over the first five weeks of the historical period, and demonstrate initial success in maintaining that increase over the last three weeks of the historical period. Thus, if mean levels of activity during observation fell below mean levels during initial maintenance, it was assumed that the participant failed to maintain changes long-term. Applying this classification scheme resulted in 25 successful maintainers who had a mean change of 55 minutes (Median = 42). In contrast, the 25 people classified as unsuccessful maintainers had a mean change of -92 minutes (Median = -67). See Table 14 for descriptive statistics and top panel of Figure 13 for a visual representation of how this classification was made for each participant. Additional detail appears in Appendix B. As can be seen from Figure 13 (bottom panel), these groups display trajectories in active minutes that adequately represent maintenance success and failure. Moving from historical to observational period, weekly mean active minutes declined for unsuccessful maintainers (red) and increased for successful maintainers (green, see Figure 13). Overall levels of active minutes were similar across groups during the observation period (for successful maintainers: $M = 362$ and $SD = 212$; for unsuccessful: $M = 341$ and $SD = 213$, see Table 14 and Figure 13). Thus, it appears that the largest difference between successful and

unsuccessful maintainers was that successful maintainers had more modest, incremental increases in active minutes during the historical period (illustrated in the bottom panel of Figure 13), which resulted in fewer active minutes during the three weeks prior to maintenance, compared to those who were unsuccessful (illustrated in the top panel of Figure 13). Thus, successful maintainers did not have as dramatic of an increase to maintain as did unsuccessful maintainers, and therefore had fewer minutes to lose (so to speak).

An alternative explanation is that the two groups were simply observed in different phases of change that were slightly staggered in time. Specifically, unsuccessful maintainers may have gone through phases of change earlier. Their peak in active minutes occurs in Week -4, which arguably marks the end of *initiation*. In contrast, successful maintainers do not hit their peak in active minutes until Week 2. Thus, they simply lag behind unsuccessful maintainers and, if observed for longer, would similarly return to lower levels of activity. A similar alternative is that the two groups differ not in maintenance success and failure, but in their rate of change and variability, with those classified as unsuccessful changing (positively and negatively) more rapidly, and bouncing frequently from high to lower levels. The study eligibility criteria were carefully designed to capture a sample of people in the *same* phase of change, which makes the second alternative more plausible than the first. In what follows, I explore how these two groups differ in trajectory of motivation and habit variables.

Table 14. Descriptive statistics for mean activity minutes during three weeks preceding observation and observation, and among successful and unsuccessful maintainers.

| var # | vars | n | M | SD | min | Q1 | med | Q3 | max | skew |
|---------------------------------|---------------------------------------|----|-----|-----|------|-----|-----|-----|------|-------|
| <i>Successful Maintenance</i> | | | | | | | | | | |
| 1 | Last three weeks of historical period | 25 | 306 | 198 | 15 | 152 | 290 | 459 | 686 | 0.31 |
| 2 | Observation period | 25 | 362 | 212 | 56 | 188 | 306 | 492 | 796 | 0.38 |
| 3 | Change from 1 to 2 | 25 | 55 | 44 | 5 | 24 | 42 | 77 | 193 | 1.28 |
| <i>Unsuccessful Maintenance</i> | | | | | | | | | | |
| 1 | Last three weeks of historical period | 25 | 434 | 271 | 165 | 276 | 349 | 472 | 1304 | 1.66 |
| 2 | Observation period | 25 | 341 | 213 | 117 | 192 | 286 | 413 | 972 | 1.24 |
| 3 | Change from 1 to 2 | 25 | -92 | 134 | -705 | -97 | -67 | -35 | -8 | -3.80 |

Note: Descriptive statistics are rounded to nearest integer. Active minutes are the sum of “fairly” and “very” active minutes readouts from each participant's Fitbit, and are earned for activities at or above 3 metabolic equivalents. The measure is often used as an estimate of time spent in moderate-to-vigorous physical exercise.

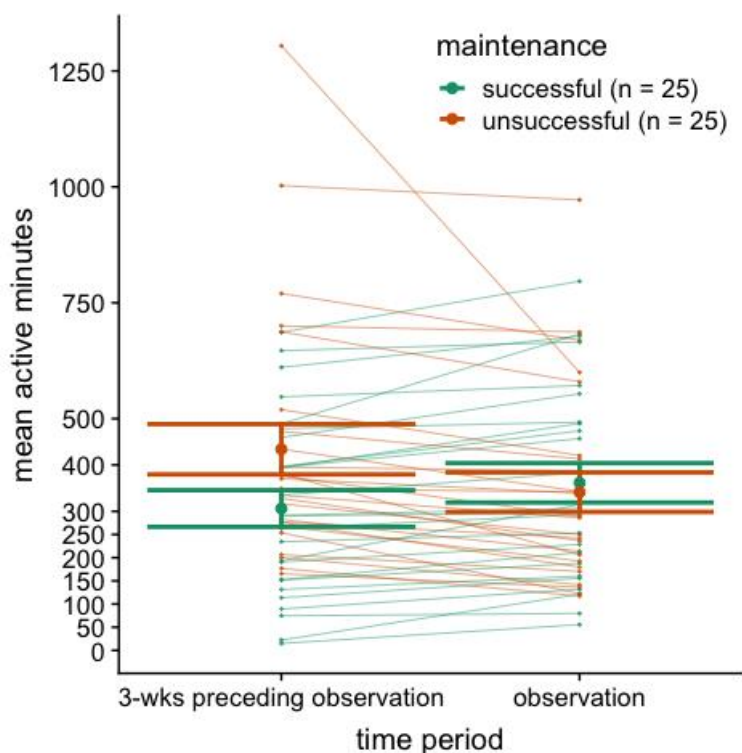
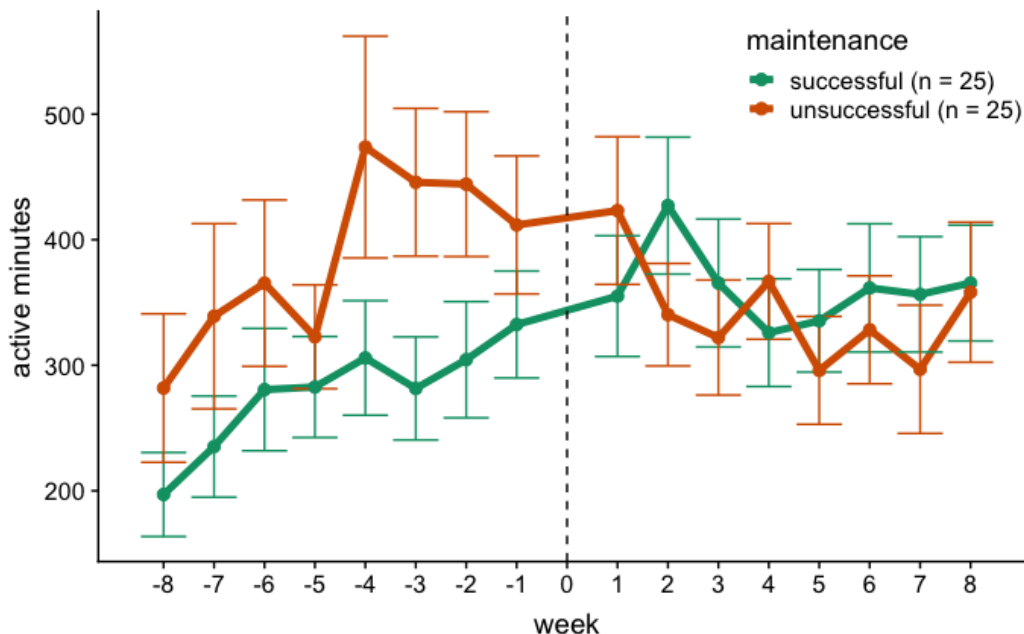


Figure 13. Comparison of activity level for successful and unsuccessful maintainers. Above: Individual mean change from three weeks preceding observation to 8-week observation period. Below: Weekly activity by group.

Note. **Below:** Solid lines are mean weekly active minutes with standard error depicted. Weeks -8 through -1 are on the x-axis represent the historical period, and weeks 1 through 8 represent the observation period. **Above:** Each participant's change in mean activity minutes from three weeks preceding observation to 3-week observation period is plotted. The thick point represents group mean with standard error depicted.



1.16.5.3 Differences in the trajectory of motivation and habit variables for successful and unsuccessful maintainers

Time-series plots of the differences between successful and unsuccessful maintainers for each of the motivation and habit variables are depicted in Figure 14 and 15. Weekly mean value for each variable is plotted by group with standard error bars also depicted. In what follows, I make observations based on visual inspection of difference between the two groups within-variables and between-variables.

Group differences within-variable. These trends are most easily observed in Figure 14. First, specific satisfaction started at similar levels for each group, and diverged over time, such that successful maintainers were slightly more satisfied than were unsuccessful maintainers by the last two weeks. Automaticity of instigation and performance followed the same trend: The groups diverged over time, such that successful maintainers were at higher levels by the final two weeks. For all other variables, the groups did not differ in trajectory.

Group differences between-variables. There is a difference between groups across context stability and automaticity variables, which is most easily observed in Figure 15. Among successful maintainers, context stability and automaticity were at a similar level throughout the study. In contrast, for unsuccessful maintainers, automaticity was meaningfully lower than context stability throughout the study.

Taken together, results suggest that people who were able to maintain higher levels of specific satisfaction and automaticity appear more likely to sustain an increase in exercise over time. In what follows, I revisit evidence for hypotheses and hypothetical scenarios of Figure 6.

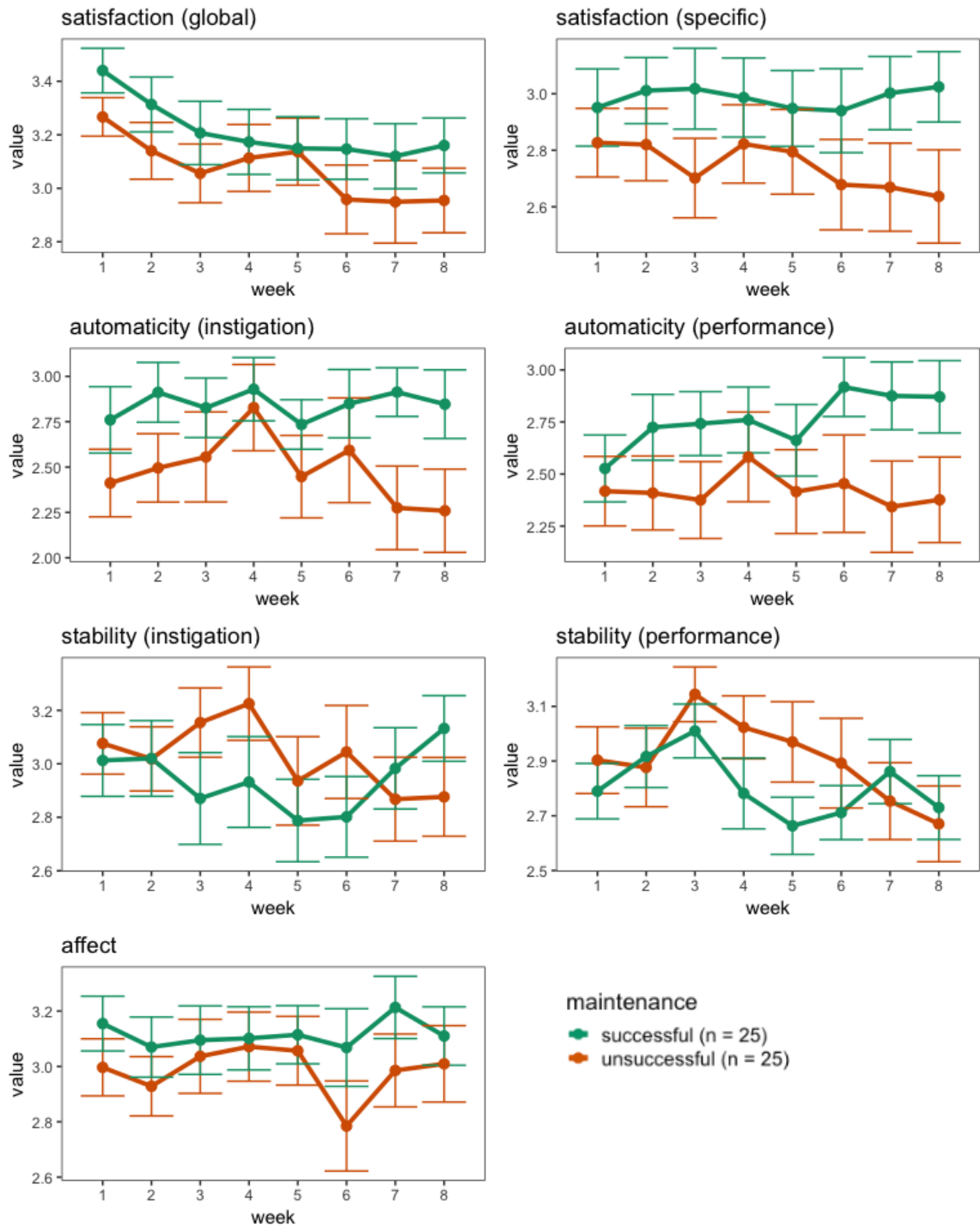


Figure 14. Time-series of each variable by successful and unsuccessful maintenance

Note: Solid lines are weekly mean value for each variable during the observational period by group. Bars around the mean represent the standard error.

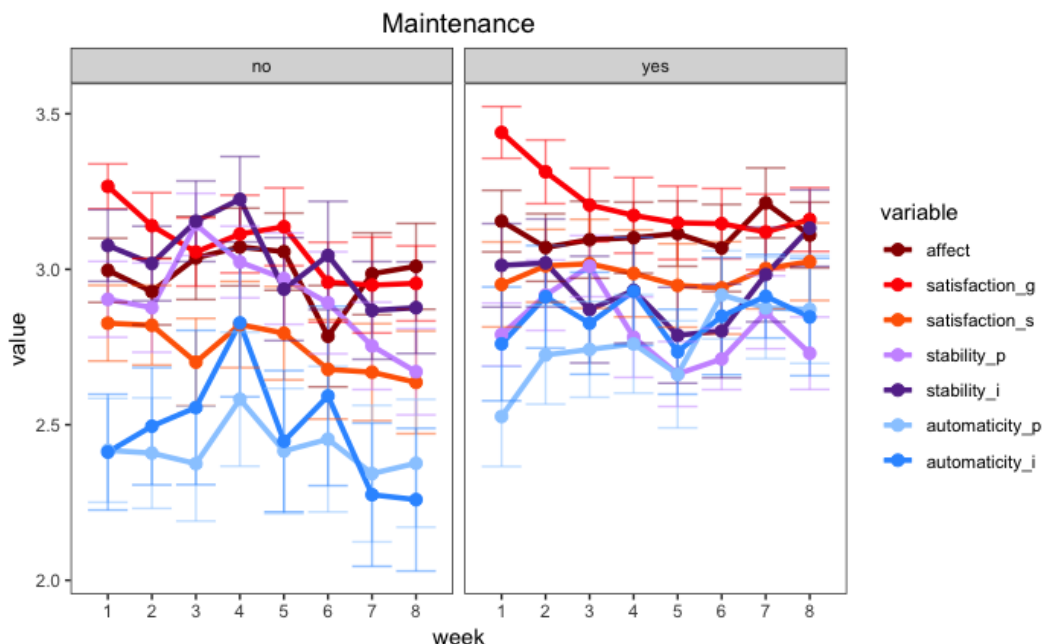
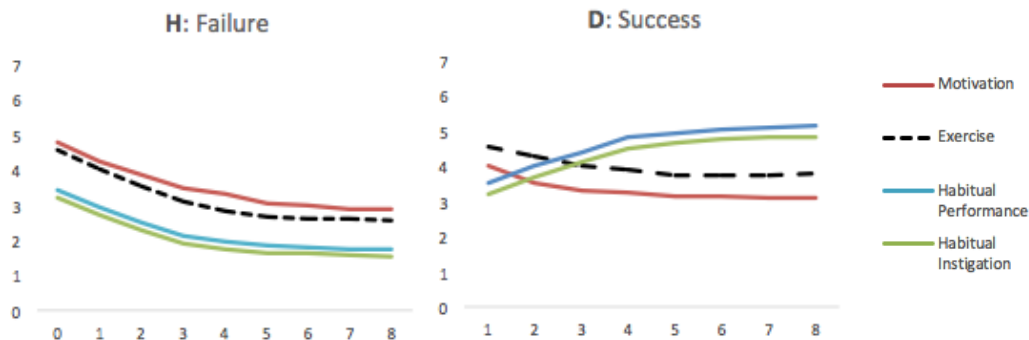


Figure 15. Observed (above) and hypothesized (below) scenarios depicting successful and unsuccessful maintenance for motivation and habit variables

Note: Hypothesized scenarios H and D are reprinted from above. They are the two scenarios that most closely correspond to observed data; although they do not perfectly capture observed patterns.



Revisiting hypothetical scenarios, A through H. The observed trend among successful maintainers (top-right panel of Figure 14) fails to align with any of the scenarios, but is most closely captured by Hypothetical Scenario D (bottom-right panel). The hypothesis of Scenario D was that successful maintenance would be characterized by increases in habitual instigation and performance, which hang together over time, and by decreases in motivation over time such that it stays at middling levels. With a few

exceptions, the observed data follow this trend. First, levels of habituation do not surpass those of motivation. Second, habit variables differentiated successful maintainers from unsuccessful ones, but only for the automaticity measure. Further, automaticity did not increase for successful maintainers; rather, it was higher and remained the same in contrast to lower levels and decline among unsuccessful maintainers. Third, not all motivation variables declined; only global satisfaction did. Furthermore, as discussed above, maintaining (as opposed to declines in) specific satisfaction over time appeared to differentiate successful maintainer from unsuccessful ones.

The observed trends among unsuccessful maintenance (top-left panel of Figure 15) most closely aligns with Hypothetical Scenario H of (bottom-left panel). The hypothesis of Scenario H was that all variables decline (asymptotically) over time, which results in unsuccessful maintenance. This was the case for some, but not all variables. As mentioned above, global satisfaction clearly declined for unsuccessful maintainers, and so did specific satisfaction and automaticity relative to successful maintainers.

Revisiting Hypotheses, 1-4. Regarding Hypotheses 1-4, the observed pattern most clearly fails to support Hypothesis 2 and 3a. Hypothesis 2 states that motivation positively affects habit processes, particularly instigation, which supports maintenance. This seems unlikely considering that global satisfaction declined, and that affect and specific satisfaction remained stable, whereas automaticity and stability remained the same. Hypothesis 3a states that habitual performance undermines motivation, resulting in unsuccessful maintainers. This better describes observations in successful maintainers, though subtly and only for a few variables. Specifically, among successful maintainers—compared to unsuccessful maintainers—motivation declined (global satisfaction) or

stayed the same (affect and global satisfaction), while habituation trended upward (automaticity) or stayed the same (stability). In an early finding it was clear that within-person increases in automaticity of performance were associated with decreases in motivation. This is still possible, but perhaps that difference does not hold meaningful consequences for activity levels.

Hypothesis 4 states that successful maintenance would be characterized by increases in habitual instigation and stable/middling levels of habitual performance. This was clearly not the case for both automaticity and context stability, instigation and performance closely hung together over time for both successful and unsuccessful maintainers. Finally, Hypothesis 1 predicts that higher levels in all variable will be related to successful maintenance. This was somewhat supported, with the exception of global satisfaction, which declined for everyone, and other variables that remained stable for both groups.

1.17 Discussion of Study 2

The aim of the Study 2 was to collect naturalistic observational data to more fully understand what enables people to sustain increases in exercise long-term. The hope was to inform more nuanced theorizing on the topic, and begin to define dynamical systems model that captures these ideas in greater specificity. Several large theoretical questions were explored in great detail, such as: How does one identify people in a maintenance phase of change? Do different trajectories of habitual instigation and exercise performance hold consequence for sustaining changes? How do motivational and habitual processes interact over time? Do weekly within-person fluctuations in these variables influence activity levels? Are motivation and habit variables equally important in the

maintenance phase of change? Although the present research could not possibly speak conclusively to all of these big questions, there were findings that provide some initial tentative answers.

One clear finding was that on weeks in which automaticity of performance was higher participants exercised for longer. This aligns with the perspective that performance automaticity sustains behavior change by increasing ease of action. In other words, people exercise for longer when thinking during performance of the exercise is minimal (Sherwood & Jeffery, 2000). Thus, when exercise is a Type 1 or 3 habitual behavior (Table 2, i.e., performance is automatic, regardless of the automaticity of instigation), higher activity levels are more likely. This finding runs counter to the perspective that increasing automaticity of *instigation* while maintaining middling levels of performance automaticity (Type 2 habitual behavioral) may prolong maintenance of exercise (Gardner & Lally, 2013; Gardner, 2015). Finally, this result aligns with a large cross-sectional literature that finds correlations between time spent exercising and higher levels of automaticity ($r = 0.32$ from one review, Rebar et al., 2016).

One limitation of this finding is that its consequences for maintaining increases in exercise are not entirely clear. Maintenance success is a construct operating across more than one week. Just because activity is higher for the individual on weeks in which automaticity is higher than that individual's average does not imply that overall higher levels of automaticity or longitudinal increases in automaticity will help maintain changes. However, comparisons of successful and unsuccessful maintainers (Figures 14 and 15) provided preliminary evidence that this may in fact be the case; successful maintainers tended to exercise with greater automaticity. Additionally, there were

differences between groups in the trajectory of satisfaction, with individual-specific experiences, one operationalization of the motivational construct proposed as critical to the maintenance phase by Rothman and Colleagues (2000, 2004). Global satisfaction, which prior empirical work found to regulate maintenance success (e.g., Baldwin et al., 2006), was not related in this study. Furthermore, the fact that both automaticity and satisfaction played a role in sustaining increases in exercise, provides initial support for the idea that in the case of complex behaviors, both constructs (instead of just satisfaction) are active during the maintenance phase.

One surprising finding was that aside from performance automaticity, there were no other direct associations between motivation/habit variables and weekly exercise (see Table 11). There are a few possible explanations. First, ceiling effects may have obscured the association, particularly for motivation variables, which had averages near the top of the scale. Second, large between-person differences in overall-levels of exercise may have washed out subtle effects of psychological variables. Third, the sample size may be too small to detect what may be small effects. Fourth, the low within-person variance for psychological variables could have made it hard to detect effects. This may also be a property of the measures; they simply do not vary much week-to-week, and assessments on the scale of months or years are needed to observe differences. Future research should explore this possibility.

Another finding that failed to align with theory and past research (Gardner & Lally, 2013; Gardner, 2015) was that habitual instigation and performance did not follow different trajectories for successful and unsuccessful maintainers. It was expected that increases in instigation coupled with middling or lower levels of performance that does

not increase, may characterize successful maintenance. However, measures of instigation and performance tended to hang together over time. Relatively high correlations between performance and instigation for both automaticity ($r(49) = .66, p < .001$) and context stability ($r(49) = .66, p < .001$) may indicate that theoretical-conceptual differences are not empirically distinct enough, at least using the most common and contemporary measurement approach. Similarity of these measures may have made it challenging to observe expected differences in their association with exercise. This caveat aside, prior research (Phillips & Gardner, 2016) yielded a similarly high correlation between exercise instigation and automaticity ($r(119) = 0.67, p < .001$), but the two measures loaded onto different factors, and were differentially associated with exercise maintenance.

Another surprising result was that there was substantial variability between participants in overall activity minutes. One implication is that among people who already exercise a lot, initiating and maintaining an increase may look very different psychologically compared to people who are starting at lower to no activity. Furthermore, the theoretical concepts of interest to this study may not be as relevant among already highly active people. To my knowledge, no theories of sustained change for physical activity are explicit about whether predictions depend on the baseline activity level. However, it seems reasonable to assume that highly active people may already be high and stable in motivational and habit variables. Future research should take measures to restrict recruitment to people who are starting at lower levels of activity.

A final finding of importance was that higher motivation was associated with higher habituation, between person. Several empirical studies have observed that increases in affect are associated with increase in automaticity during the maintenance

phase of change (e.g., Phillip et al., 2016). Interestingly, the within-person relation was in the opposite direction. On weeks in which habituation (particularly automaticity) was higher, motivation was lower. This aligns with theory and empirical results derived from Gardner and colleagues (2013; 2015) that high levels of performance automaticity may undermine motivation, though it appears not do so to detriment of activity levels.

Considering these results together, Study 2 provide a rich picture of how motivation, habituation, and exercise interact during a maintenance phase of change.

1.17.1 Additional Strengths and Limitations

A clear strength of the present study is the careful, highly specific definition of the maintenance phase of change for physical exercise, which enabled highly focused recruitment and observation of people in this phase. Additionally, to my knowledge, no other study has attempted to evaluate in such rich longitudinal detail how the measures most commonly theorized to sustain increases in exercise evolve months after a change is made. The study also has strong ecological validity; processes were examined naturalistically with minimal intrusion (e.g., participants increased exercise of their own volition prior to hearing of the study and were simply asked to continue exercising as they normally would).

The length of the study is another strength. Sixteen weeks of daily accelerometer estimates of exercise in addition to eight weeks of regular psychological survey data is uncommon. However, it could be argued that a longer historical and observational period are needed to be certain participants were in a maintenance phase of change as intended. As discussed previously, it is possible that an additional eight weeks of data would reveal

that those who were classified as successful maintainers may also return to baseline levels of activity.

There are also limitations regarding inferences from these data. The observational nature of the study precludes conclusions about the direction of associations. Second, the exploratory nature of the study and limited sample size highly constrain the drawing of conclusions from inferential statistics. The objective of the study was primarily to serve as a guide for future theorizing in a domain in which there is little guidance from data that are naturalistically collected, longitudinal, and observational (see Figure 3).

1.18 Synthesizing Methods of Study 1 with Results of Study 2

As described in the section on Study 1, a dynamical systems model (Figure 4) was simulated in an attempt to identify parameters and a scenario that adequately describe the evolution of motivational and habitual variables as a person attempts to maintain increases in exercise. Results from Study 2 were used to inform the refinement and further simulation of the dynamical systems model of Study 1. The objective was to specify a model that accurately represents theoretical understanding of sustained increases in exercise, and the relations observed in Study 2. This was attempted, but the current work fell short of identifying an adequate model. In what follows, I describe the process and results, and then discuss challenges, opportunities, and lessons learned.

The dynamical systems model presented in Figure 4 of Study 1 was specified in MATLAB 2017b using differential equations (e1) through (e5), and a regression problem was simulated using the following process. The parameters for each equation (e1 – e5) were solved for. For example, e3 was as follows:

$$\tau_3 \frac{d\eta_3}{dt} = -\eta_3(t) + \beta_{31}\eta_1(t) + \beta_{32}\eta_2(t) + \beta_{34}\eta_4(t) + \beta_{35}\eta_5(t) + \gamma_3\xi_3(t)$$

As a reminder, $\eta_1, \eta_2, \dots, \eta_5$ represent each of the five variables in the model: affect (η_1), satisfaction (η_2), exercise (η_3), habitual performance (η_4), and habitual instigation (η_5).

Set $\tau_3 = 1 \text{ week}$

Then e3 can be rewritten:

$$\begin{aligned} \eta_3(k+1) - \eta_3(k) \\ = \frac{-\eta_3}{\tau_3}(k) + \frac{\beta_{31}}{\tau_3}\eta_1(k) + \frac{\beta_{32}}{\tau_3}\eta_2(k) + \frac{\beta_{34}}{\tau_3}\eta_4(k) + \frac{\beta_{35}}{\tau_3}\eta_5(k) + \frac{\gamma_3}{\tau_3}\xi_3(k) \end{aligned}$$

$$\text{Set } \tau_3 = -\frac{1}{\theta}$$

Solving for each parameter results in the following:

$$\beta_{31} = -\frac{\theta_2}{\theta_1}; \quad \beta_{32} = -\frac{\theta_3}{\theta_1}; \quad \beta_{34} = -\frac{\theta_4}{\theta_1}; \quad \beta_{35} = -\frac{\theta_5}{\theta_1}; \quad \gamma_3 = -\frac{\theta_6}{\theta_1}$$

This was done for differential equations (e1) through (e5). Simulations were then conducted to predict $\eta_1, \eta_2, \dots, \eta_5$ from “measured” data. Measured data was a dataset with values for each of the five variables over time. This dataset can be generated from observed patterns in how variables evolved over time (e.g., the patterns observed in Figure 15) or from theoretical expectations. The result of this simulation was a time-series plot for each variable with lines representing the measured data and the models predicted fit of these data. Additionally, the simulation results in estimates for each parameter in the model.

An example of results from one simulation is presented in Figure 16. On the y-axis is the value for each of the variables, which was allowed to remain arbitrary. On the x-axis is weeks, which was extended to 16 (instead of the 8 used in Study 2). One of the first things that became clear during simulations was that additional weeks were need for

a better fit. In general, many observations are needed for modeling with the dynamical systems approach (at least two times the number of variables being modeled, but ideally many more; Rivera, 2018). As can be seen in Figure 16, predictions fit measured data well for exercise (η_3), which starts low and then increases rapidly over time, eventually plateauing (a reasonable representation of what the trajectory of exercise might look like for a successful maintainer). Affect (η_1) behaves similarly, starting low and then increasing rapidly before plateauing. Satisfaction (η_2) and habitual instigation (η_4) increase linearly over time, whereas habitual performance (η_5) is more erratic and increasing in a step-wise fashion. This was the best simulation result from attempts to generate any measured data that the model could predict with accuracy. This was challenging, in and of itself, let alone matching results of Study 2 to the model.

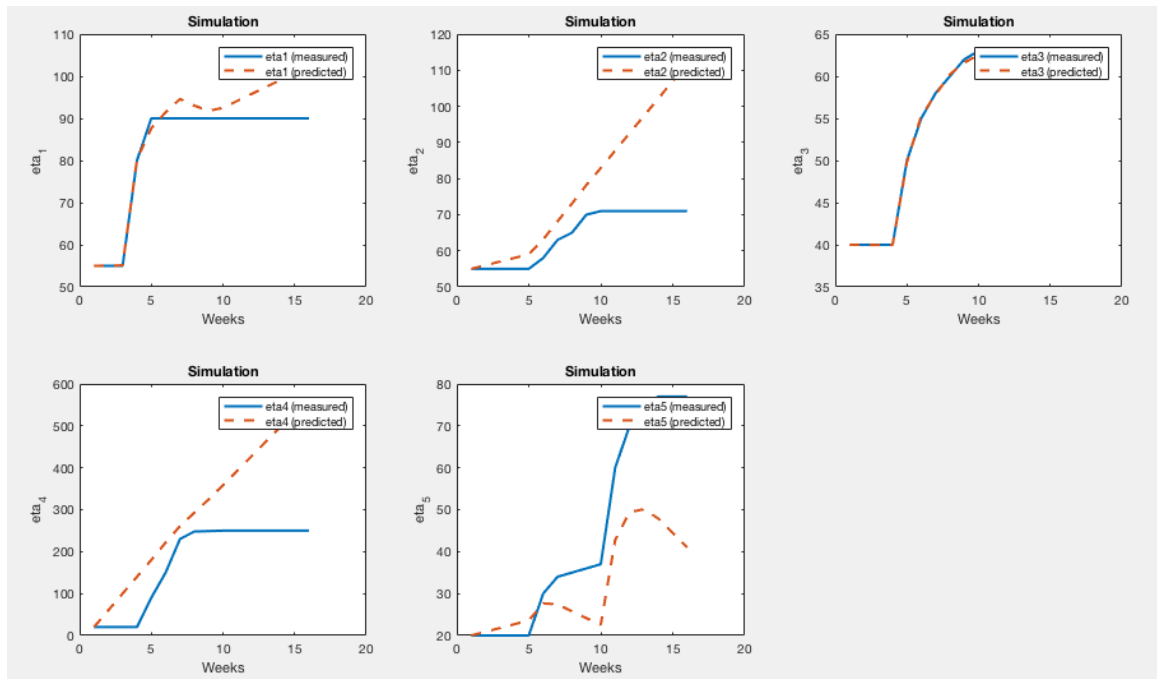


Figure 16. Scenario resulting from simulated model.

Note: η (eta) represents the following variables depicted in the model of Figure 4: affect (η_1), satisfaction (η_2), exercise (η_3), habitual performance (η_4), and habitual instigation (η_5). The y-axis is the value for each of the variables, which was arbitrary. On the x-axis is weeks, which was extended to 16 (instead of the 8 used in Study 2).

Several changes to the model in Figure 4 were also simulated in an attempt to match results of Study 2. For example, paths were removed from the model, and the two habit variables were collapsed into a single variable. However, results from Study 2 were less informative than expected. For example, automaticity of performance was the only variable associated with changes in exercise, which suggests that paths from motivation variables to exercise be removed. Additionally, negative associations between motivation and automaticity were found. The dynamical system presented in Figure 17 could potentially represent these results. However, results from these simulations did not represent the observed trends in Study 2. They simply led to growth in automaticity and exercise, similar to that reflected in Figure 16. Furthermore, it is unclear how to represent the finding from Study 2 that specific satisfaction and automaticity were higher and steadier for successful maintainers than for unsuccessful maintainers, who saw slight declines. Caveats aside, a strength of the model in Figure 17 is that it aligns well with prior studies. For example, Phillip and colleagues (2016) found that among people in the maintenance phase of change, motivation predicted automaticity which, in turn, predicted exercise (see also Radell et al., 2017). Additionally, including only one feedback path from exercise to automaticity makes the clearest theoretical sense; automaticity is explicitly theorized to arise (at least in part) through repetition of exercise (Gardner, 2015; Hagger, 2019). Furthermore, introducing or removing other feedback paths reduces the sensitivity of the model to small changes, and chaotic results to which dynamical models are generally predisposed.

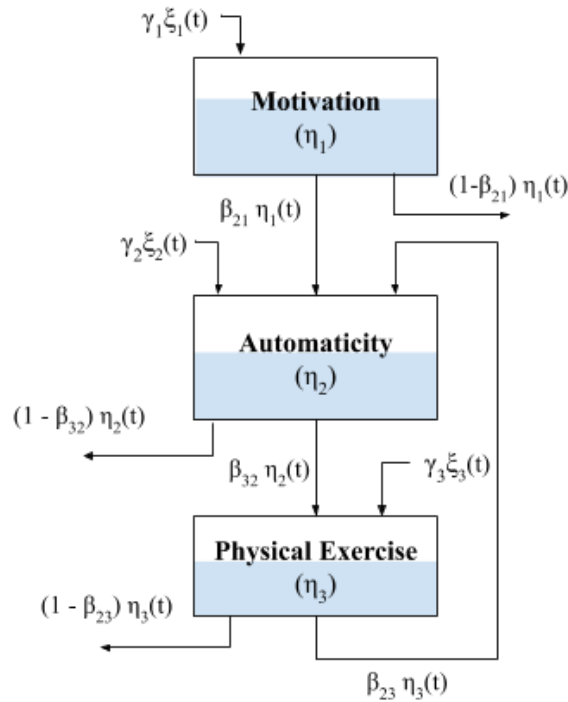


Figure 17. Modification of dynamical systems model of Figure 4 that may better represent results from Study 2.

Overall, results from simulations were highly erratic, which is common among dynamical systems (Guastello, 2001), and none of the simulations resulted in a satisfactory conclusion. Thus, relations specified in these models need further modification before they are tested in a system-identification experiment. Tuning a dynamical systems model is highly technical. There are many features and parameters that can be adjusted, any one of which can have dramatic consequences for results and for which the conceptual implications are unclear. Future simulations of this model would benefit from closer involvement of a domain expert in control systems engineering or related fields. In the following section I briefly summarize lessons learned from engaging with the dynamical systems approach, and big-picture conclusions from these two studies.

8 Concluding Remarks

The present research builds upon a conceptual framework of phases of behavior change from Rothman and colleagues (2000; 2004; 2008; see Table 1). The framework proposes that: (1) cognitions related to behavioral beliefs and intentions are of primary importance to behavioral initiation; (2) motivational processes are of primary importance to continued response and maintenance; and (3) habitual processes are of primary importance to long-term sustained change. The present research focused on the second (maintenance) and third (habit) phases of Rothman and colleagues' framework with the objective of deepening understanding of how motivational and habitual processes evolve and interact with each other as a person attempts to maintain a behavioral change.

Specifically, it was expected that the proposed constructs guiding the theoretically distinct maintenance and habit phases may be playing a more active role across phases of change. Study 2 provides preliminary evidence that both motivational and habitual processes are predictors of behavioral maintenance, and may interact with each other (e.g., on weeks in which people exercised with greater automaticity they were less motivated to exercise). However, the present work cannot speak to the entire framework proposed by Rothman and colleagues'. For example, psychological cognitions (e.g., beliefs and intentions) during initiation of changes in exercise were not examined. Furthermore, the present study attempted to observe phases of change as naturalistically as possible which made it hard to determine whether all participants were in the same phase of behavior change. Future work would benefit from introducing additional controls. For example, exclusively sampling non-exercisers and following them for long

enough to observe psychological change across all three phases of behavior change may prove fruitful. Additionally, asking participants to initiate and try to maintain increases in exercise, or experimentally intervening in this regard, may also be fruitful. Both of these suggestions for future research would help ensure participants all start in the same phase of change (which was not clearly the case in the present study despite highly specific eligibility criteria).

The present research also clearly speaks to questions regarding which of the many psychological variables are pertinent to maintaining behavioral changes in exercise, and in this regard emphatically supported theorizing from Rothman and colleagues. Among habit variables, automaticity of the performance of exercise emerged as most relevant. Among motivation variables, satisfaction with outcomes that are specific to the person was a clear winner. Future research should continue to explore the role these variables play in behavioral maintenance. The present work also highlighted a lack of a distinction between habitual instigation and habitual performance of exercise, which were expected to differentially affect maintenance. Measures of these two constructs were highly correlated and would benefit from additional psychometric research. Future research with these variables may have more success with highly controlled experimental designs that help tease apart the subtle differences, and their resulting consequence for behavioral maintenance (for preliminary work see Phillips & Gardner, 2016; Gardner, Phillips, & Judah, 2016).

The present research also attempted to capture how feedback processes might play a role during maintenance, a largely unexplored topic in health-behavior change research. It was anticipated that the dynamical systems approach would help bolster

understanding regarding feedback; however, conclusions of the present research in this regard are highly limited. In my view, the largest barrier to an understanding of feedback is that connections among a system of psychological variables are far more susceptible to change and much less observable than are connections among a system of engineering variables, the context in which the dynamical systems approach was developed. In other words, physical pipes do not connect psychological variables as they do tanks of fluid in a factory. The fluid analogy employed in the present work remains an analogy with the large assumption that “pipes” between psychological “tanks” can be observed and remain relatively stable. Additionally, not only are the connections among psychological tanks more tenuous than those connecting tanks of fluid, so too is our understanding of the substance within tanks. The dynamical systems approach is most effective when measurement is highly reliable, variables can be measured frequently and nearly instantaneously, and variables are relatively quick to change. For these reasons, all interventions using a dynamical systems approach in the health-behavior domain currently focus on variables such as daily steps and goals for daily steps, as opposed to self-reported measures of motivation and habit (for example see Hekler et al., 2018). Furthermore, feedback in the example from Hekler and colleagues (2018) is examined by rewarding goal achievement with points tied to a cash value. Thus, the “pipes” representing feedback processes are more directly apparent to the person. The person knows that achieving a step goal results in a reward, and thus feedback from goal achievement to continued behavioral response (steps), and back in a loop, is directly apparent to the person. In contrast, the present research implicitly assumes that there is feedback among variables. For example, the present work proposes that there is feedback

between engagement in exercise and the automaticity with which exercise is enacted.

However, this feedback loop is not necessarily apparent to the person, and thus is more susceptible to vary by person than the example from Hekler and colleagues (2018).

The potential benefits that could come from a dynamical systems approach are clearly constrained. However, the present research highlights at least one place in which the approach helps focus the theorist's thinking and the empiricist's planning in a way that is clearly beneficial. The approach focusses attention on issues of time and timing, which are sometimes less emphasized in health-behavior research. For example, the time scale at which theoretical constructs are expected to operate are rarely discussed, and typically only becomes explicit in the operationalization of variables and procedures in an empirical context. Some researchers highlight the importance of time and timing to health-behavior research, broadly (Hekler et al., 2016; Scholz, 2019). However, time is particularly important to behavior change maintenance, because the concept of maintenance inherently implicates time. The current research proposed that week-to-week changes in psychological variables over the course of a few months were sufficient for naturalistically observing processes of behavior change maintenance. However, results highlight that the relatively narrow time course limits conclusions and that the psychological variables failed to substantially vary week-to-week. This may be an indication that month-to-month measures of psychological variables over the course of years may be required to accurately capture naturalistic processes of behavior change maintenance.

The potential for the dynamical systems approach to augment traditional theories of health behavior change are staggering. However, realizing the potential is challenging

and also highly constrained by factors such as unreliable measurement that still plague psychological science. It is clear from the present work that the approach encourages greater precision and more careful theorizing regarding where, when, for whom, and in what psychological state a theory's mechanism of action will produce an effect (Heckler et al., 2016). In addition, it encourages careful thinking about time and timing of theoretical processes, and the constructs in one's theory—how they are defined, connected to one another, and change over time. However, realizing the full potential of this approach—formalizing theoretical propositions into mathematical equations, modeling feedback, and implementing an adaptive intervention informed by the model—requires a level of nuance, empirical data, and expertise that takes time, resources, and collaboration that is difficult to cultivate. Forwarding knowledge of the processes that guide maintenance of health behavior change will require expensive, large, and lengthy studies orchestrated by interdisciplinary teams. The challenge is exacerbated by a topic with constructs that are hard to define, unreliably measured, and hard to assess in high frequency (see Hekler et al., 2018 for the most comprehensive review of constraints and current initiatives). The present work attempted to take small step in the direction of formalizing and implementing a more nuanced theory of psychological processes that sustain health behavior change, but primarily highlighted the challenge of doing so. I remain cautiously optimistic that investing resources in a dynamical system approach to health-behavioral theory will eventually inform interventions that effectively help people realize long-term lifestyle changes critical to health.

9 References

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Appendix A: Study 2 Questionnaires, Codebook, & Materials

Description of Contents

This appendix contains all questionnaires used in Study 2. Questionnaires were exported from Qualtrics and include consent forms, study instructions, skip logic, embedded data, variable names, and response values. Thus, the following materials can also be used as a codebook.

Screener Survey (Figure 7, T0ab)

Survey Flow

| |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <p>EmbeddedData SIDValue will be set from Panel or URL. PIDValue will be set from Panel or URL. RIDValue will be set from Panel or URL. RdateValue will be set from Panel or URL. TIMEValue will be set from Panel or URL. TimeZoneValue will be set from Panel or URL. RTValue will be set from Panel or URL.</p> |
| <p>Block: Screener (16 Questions) Standard: Ineligible (1 Question)</p> |
| <p>Branch: New Branch If If Thank you for your interest in our study, \${name/ChoiceTextEntryValue/1}. Based on your respo... Is Displayed</p> |
| <p>EndSurvey: Advanced</p> |
| <p>Block: Consent to Access Data (Form A (T0b) (4 Questions) Block: setup data share (8 Questions)</p> |
| <p>EndSurvey: Advanced</p> |

Page

Break

Start of Block: Screener

Exercising with Fitbit Study
University of Minnesota

Thank you for your interest!

The purpose of this survey is to determine whether you are eligible to participate.

It is important that you answer the following questions accurately and honestly. Your responses will be used again later in the study.

Before we begin, please enter your name and sign below to certify that you will answer this questionnaire truthfully.

☐ First Name (1) _____

☐ Last Name (2) _____

signature I certify that I will answer this questionnaire truthfully.

Page _____

Break

geo.us Do you currently reside in the United States of America?

☐ Yes (1)

☐ No (0)

t0a.demo.age How old are you? (enter years)

t0a.occupation What is your occupation?

t0a.work.pa Does your occupation involve strenuous physical activity?

- ☐ Often (3)
- ☐ Sometimes (2)
- ☐ Rarely (1)
- ☐ Never (0)
-

t0a.disable Do you have any disabilities, diseases, injury, or illness that regularly prevents you from engaging in strenuous physical exercise?

- ☐ Yes (1)
- ☐ No (0)
-

t0a.sport Do you engage in physical activity as part of an organized sports team?

For example: intramural basketball, or club soccer.

The following don't count as organized sports: pick-up basketball, yoga or spin class, casual running/cycling groups, etc.

- ☐ Yes (1)
- ☐ No (0)
-

t0a.phonetext Do you have a smartphone that can receive text messages? And, are you willing to respond to text messages as a part of this study?

☐ Yes (1)

☐ No (0)

t0a.phone.internet Does your smartphone have cellular service with a data plan or access to the internet (or wifi)?

☐ Yes (1)

☐ No (0)

t0a.demo.fitwear
Over the last 2 months, how regularly did you wear a Fitbit?

☐ Every day (5)

☐ Nearly every day (4)

☐ Very often (3)

☐ Often (2)

☐ Rarely (1)

☐ Never (0)

t0a.fithr Does your Fitbit monitor your heart rate? If you don't know, please check your Fitbit.

☐ Yes (1)

☐ No (0)

t0a.demo.fitttype What type of Fitbit have you been wearing?

- ☐ Alta HR (1)
- ☐ Charge 1 HR (2)
- ☐ Charge 2 HR (3)
- ☐ Charge 3 HR (4)
- ☐ Versa (5)
- ☐ Ionic (6)
- ☐ Other: (7) _____

Page _____

Break

t0a.attemptincrease Fitbits recognize physical activities that are more strenuous than regular walking. You earn **active minutes** for doing these strenuous activities. If you have many active minutes in a day, you earn an **active day** on your Fitbit dashboard.

Active minutes are often earned during **cardiovascular exercise** which involves activities that **noticeably increase your heart rate**. This includes weight training, running, biking, swimming, or strenuous yoga.

Active minutes can also be earned during **incidental** physical activity which involves life-related tasks that happen to increase your heart rate, such as walking up stairs or carrying groceries.

We are interested in your cardiovascular exercise, NOT incidental physical activity.

At any point over the last 2 months have you **consciously attempted to increase** your active minutes or active days per week by engaging in more cardiovascular exercise?

- ☐ Yes (1)
- ☐ No (0)

Display This Question:

If t0a.attemptincrease = 1

t0a.increase As a result of your attempt to increase cardiovascular exercise, have your total active minutes per week increased over the last 2 months?

- ☐ Yes (1)
- ☐ Maybe (2)
- ☐ No (0)
-

Display This Question:

If t0a.increase = 1

Or t0a.increase = 2

t0a.increasecheck Please check that your active minutes seem to have increased recently. Later, our research team will verify that your Fitbit data qualifies you for the study.

Here's how you check...

Open Fitbit App: select the lightning bolt symbol, tap on the bar graph, then select “3 mo” at top of bar graph.

Have the bars been increasing week-to-week? Does the amount of activity in the last month appear greater than the month before that? If so, you have successfully been increasing your active minutes. Please select “yes” below.

Select "unsure", if you are having trouble locating this information, or are unsure whether you've increased activity.

- ☐ Yes (1)
- ☐ Unsure (2)
- ☐ No (0)

End of Block: Screener

Start of Block: Ineligible

Display This Question:

If geo.us = 0

Or How old are you? (enter years) Text Response Is Less Than 18

Or How old are you? (enter years) Text Response Is Greater Than 64

Or t0a.work.pa = 3

Or t0a.disable = 1

Or t0a.sport = 1

Or t0a.phonetext = 0

Or t0a.phone.internet = 0

Or t0a.demo.fitwear = 0

Or t0a.demo.fitwear = 1

Or t0a.fithr = 0

Or t0a.attemptincrease = 0

Or t0a.increase = 0

Or t0a.increasecheck = 0

ineligible

Thank you for your interest in our study, [\\${name/ChoiceTextEntryValue/1}](#).

Based on your response you do not qualify for the study. Questions? Please contact:
fitstudy@umn.edu

Thanks for taking the time.

End of Block: Ineligible

Start of Block: Consent to Access Data (Form A (T0b))

t0b.intro

Congratulations, [\\${name/ChoiceTextEntryValue/1}](#)!

It looks like you are probably eligible to participate in the study.

But first, our research team needs to verify that your Fitbit data qualify you for enrollment. Please read the form on the next page before agreeing to give our research team access to your Fitbit Data.

t0b.consent.time Timing
 First Click (1)
 Last Click (2)
 Page Submit (3)
 Click Count (4)

t0b.consent

University of Minnesota
 Exercising with Fitbit Study
 (Fit Study, STUDY00005835)
Consent to Access Data

Investigator Team Contact Information:

For questions about research appointments, the research study, research results, or other concerns, contact the study team at:

Investigator Name: Alexander Rothman
 Investigator Departmental Affiliation: Psychology
 Email Address: roth001@umn.edu
 Student Investigator Name: Richie Lenne
 Email Address: ledon004@umn.edu

Supported By: This research is supported by University of Minnesota's Doctoral Dissertation Fellowship.

Information About This Research Study

The purpose of the following information to help you decide whether or not to be a part of this research study.

What is research?

The goal of research is to learn new things in order to help people in the future. Investigators learn things by following the same plan with a number of participants, so they do not usually make changes to the plan for individual research participants. You, as an individual, may or may not be helped by volunteering for a research study.

Why am I being invited to take part in this research study?

We are asking you to take part in this research study because you indicated interest by responding to our online listing, and you met eligibility as determined by the questionnaire you just completed.

What should I know about a research study?

Whether or not you take part is up to you. You can choose not to take part. You can agree to take part and later change your mind. Your decision will not be held against you.

You can ask all the questions you want before you decide by emailing FitStudy@umn.edu.

Why is this research being done?

The purpose of this research is to explore psychological factors related to changes in physical exercise over time. Sustaining levels of exercise that meet national guidelines is challenging to do, especially for long periods of time. We are interested in understanding what helps people sustain higher levels of exercise. This research will improve our understanding of how to help people maintain levels of exercise that are good for long-term health.

How long will the research last?

We expect that you will be in this research study for two months. The total estimated time commitment is 100 minutes. This includes a 15-minute survey upon enrollment in the study and another 15-minute survey in two months, at the end of the study. In addition, you'll be asked to complete 3-minute surveys on your phone three times/week for two months, amounting to 72 minutes spread over eight weeks.

What will I need to do to participate?

There are two parts to the study. The first part involves giving the research team secure access to your Fitbit data to verify that you are eligible for the study. This involves creating a new password for your Fitbit account and securely sharing it with the research team. The research team will only use physical activity data on your account (no other data will be used). Once access to your account has been securely shared, you will be informed of your enrollment status by email within 5 business days. If you are eligible to participate, the email will contain a link with information on how to proceed to Part 2. If you are ineligible, you will be instructed to reset your password, and our research team won't keep any of your data.

The second part of the study involves responding to survey questions and setting up a mobile texting application (15-minutes). You will then be asked to keep exercising with your Fitbit as you normally would for the next two months. On three randomly selected evenings each week, you will receive a text message at 7:00 PM with a link to complete a 3-minutes survey. Throughout this time the research team will have access to your physical activity data on your Fitbit account. At the end of two months, a final 15-minutes survey will be emailed to you. After completing this survey, you will be instructed on how to end participation, and you will receive compensation via email. Is there any way that being in this study could be bad for me? There are no known risks associated with participating in this study. As a part of this study you will be asked to exercise as you normally would. You may discontinue your participation in this study at any time without penalty. Please send us an email if you decide to discontinue participation.

Will being in this study help me in any way?

We cannot promise any benefits to you or others from your taking part in this research. However, possible benefits include improved wellness that can come from regularly

exercising. Also, we will ask you to reflect on your exercise habits, and thus you may learn about routines or thought partners that help you exercise more.

What happens if I do not want to be in this research?

There are no known alternatives, other than deciding not to participate in this research study.

What happens to the information collected for the research?

Efforts will be made to limit the use and disclosure of your personal information, including research study and medical records, to people who have a need to review this information. We cannot promise complete confidentiality. Organizations that may inspect and copy your information include the Institutional Review Board (IRB), the committee that provides ethical and regulatory oversight of research, and other representatives of this institution, including those that have responsibilities for monitoring or ensuring compliance. We will not ask you about child [or vulnerable adult] abuse, but if you tell us about child [or vulnerable adult] abuse or neglect, we may be required or permitted by law or policy to report to authorities.

Secure Storage of Data Collected

Your data from participating in this research will be stored securely by the University of Minnesota, which may include electronic storage with a University-approved third-party provider. Your research records will be labeled with a code number, your date(s) of participation in the research, name, and email address. A security breach (break in or cyber-attack) might lead to someone being able to link you to your data. This risk is very low because your data are stored securely, and the information about your identity is stored separately from the other information which can be linked only through a code.

Data Sharing

In keeping with best practices in science, we plan to make selected parts of this study's dataset publicly available when the study is complete. The dataset will be stored in a scientific data repository for an indefinite period of time. These data will primarily be accessed by other scientists, and even then, that will be rare. Nevertheless, it will be possible for anyone to download the dataset from this study. The dataset we release to the public or other investigators will, to the best of our knowledge, not contain information that can directly or easily identify you. We will remove or change information that could directly or easily identify you before files are shared. The dataset we release to the public or other investigators can be used for other, future research projects without your additional consent. Those future projects can focus on any topic that might be unrelated to the goals of this study. Once the dataset has been posted to a repository it cannot be withdrawn or recalled.

Whom do I contact if I have questions, concerns or feedback about my experience?

This research has been reviewed and approved by an IRB within the Human Research Protections Program (HRPP). To share feedback privately with the HRPP about your research experience, call the Research Participants' Advocate Line at 612-625-1650 or go to <https://research.umn.edu/units/hrpp/research-participants/questions-concerns>.

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Will I be compensated for my participation?

If you agree to take part in this research study, we will pay you **\$15 (Amazon Gift Card)** at the end of the two-month study with a chance for more compensation. If you complete the final survey and respond to 80% or more of the short surveys over the study weeks, you will receive a **\$10 bonus**, to total **\$25 in Amazon gift cards** at the end of the two-month study.

Checking "yes" below and signing the next page documents your permission to take part in this research. You will be emailed a copy of this document.

- ☐ Yes, I consent to giving the research team access to my Fitbit data for the study, and I am at least 18 years old. (1)
- ☐ No, I don't consent, or I don't want to participate (0)

Skip To: End of Survey If t0b.consent = 0

Skip To: t0b.consent = 1

Display This Question:

If t0b.consent = 1

t0b.consent = 1 Please sign that have read and consent to the above:

End of Block: Consent to Access Data (Form A (T0b))

Start of Block: setup data share

t0b.setup Thank you, \${name/ChoiceTextEntryValue/1}!

Let's get you set up!

t0b.email What is your email address? This study requires you to respond to emails. Please enter one you check frequently.

Page


Break

t0b.pass.intro As mentioned previously, in order to participate in this study our research team needs access to the physical activity data on your Fitbit account.


Please take a moment to create a new password for your Fitbit account.

Instructions are pictured below.

FITBIT APP

- 1 From the Fitbit app dashboard, tap or click the Account icon ().
- 2 Scroll down and tap or click **Security and Login > Change Password**.
- 3 In the **Current Password** box, type your current password.
- 4 In the **New Password** and **Confirm Password** boxes, type your new password.
- 5 Tap **Change**.

FITBIT.COM DASHBOARD

- 1 Log into your fitbit.com dashboard and click the gear icon ().
- 2 Click **Settings**.
- 3 Click **Reset Password**. An email is sent to your email address. If you don't receive it, it's possible the email went to your Spam or Junk folder. Check all your email folders. Make sure the email address listed in your personal info is correct. If after 24 hours you still haven't received your email, contact [Customer Support](#).
- 4 Click the link in the password reset email.
- 5 Enter your new password and click **Set**.

t0b.pass1 **Please enter your new password.**

NOTE: Once you make a new password, do not change it until the study has end or your participation in the study is discontinued. This information will be stored securely. We will only keep this information for the duration of the study, after which we will notify you to change your password again, and we will delete the password you gave us.

t0b.pass2 Please re-enter your new password. To confirm it was entered correctly.

Page

Break

t0b.emailo We will use the following email address to contact you: `#{t0b.email/ChoiceTextEntryValue}`

Is this the same email address associated with our Fitbit account?

☐ Yes (1)

☐ No (0)

Display This Question:

If t0b.emailo = 0

t0b.email.fit Enter the email associated with your Fitbit Account:

End of Block: setup data share

Intake Survey (Figure 7, T0c)

Survey Flow

| |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <p>EmbeddedData SSIDValue will be set from Panel or URL. PIDValue will be set from Panel or URL. SMSValue will be set from Panel or URL. DAYValue will be set from Panel or URL. SIGValue will be set from Panel or URL. RDateValue will be set from Panel or URL. TIMEValue will be set from Panel or URL. RTValue will be set from Panel or URL. TimeZoneValue will be set from Panel or URL. RIDValue will be set from Panel or URL. DateTakenValue will be set from Panel or URL. TriggerResponseIDValue will be set from Panel or URL. TriggerSurveyIDValue will be set from Panel or URL. ExercisesValue will be set from Panel or URL. rdayValue will be set from Panel or URL. rsigValue will be set from Panel or URL. Exercise ReasonsValue will be set from Panel or URL.</p> |
| <p>Block: Default Question Block (34 Questions) Standard: register survey signal (2 Questions)</p> |
| <p>EndSurvey: Advanced</p> |
| <p>EmbeddedData enddateValue will be set from Panel or URL.</p> |

Page

Break

Start of Block: Default Question Block

t0c.meta Browser Meta Info

Browser (1)

Version (2)

Operating System (3)

Screen Resolution (4)

Flash Version (5)

Java Support (6)

User Agent (7)

t0c.welcome

Welcome \${e://Field/RecipientFirstName}!

You are invited to participate in a study on cardiovascular exercise using a Fitbit device. You were selected as a possible participant because you met eligibility criteria and indicated your interest in the study.

Please read the consent form on the next page before agreeing to continue.

Note: it is the same as the consent form you have seen already. We are required to present it again.

| | |
|------------------|--------|
| Page | |
| Break | |
| t0c.consent.time | Timing |
| First Click | (1) |
| Last Click | (2) |
| Page Submit | (3) |
| Click Count | (4) |

t0c.consent

University of Minnesota
Exercising with Fitbit Study
(Fit Study, STUDY00005835)

Informed Consent

Investigator Team Contact Information:

For questions about research appointments, the research study, research results, or other concerns, contact the study team at:

Investigator Name: Alexander Rothman
Investigator Departmental Affiliation: Psychology
Email Address: roth001@umn.edu
Student Investigator Name: Richie Lenne
Email Address: ledon004@umn.edu

Supported By: This research is supported by University of Minnesota's Doctoral Dissertation Fellowship.

Information About This Research Study

The purpose of the following information to help you decide whether or not to be a part of this research study.

What is research?

The goal of research is to learn new things in order to help people in the future. Investigators learn things by following the same plan with a number of participants, so they do not usually make changes to the plan for individual research participants. You, as an individual, may or may not be helped by volunteering for a research study.

Why am I being invited to take part in this research study?

We are asking you to take part in this research study because you indicated interest by responding to our online listing, and you met eligibility as determined by the questionnaire you just completed.

What should I know about a research study?

Whether or not you take part is up to you. You can choose not to take part. You can agree to take part and later change your mind. Your decision will not be held against you. You can ask all the questions you want before you decide by emailing FitStudy@umn.edu.

Why is this research being done?

The purpose of this research is to explore psychological factors related to changes in physical exercise over time. Sustaining levels of exercise that meet national guidelines is challenging to do, especially for long periods of time. We are interested in understanding what helps people sustain higher levels of exercise. This research will improve our understanding of how to help people maintain levels of exercise that are good for long-term health.

How long will the research last?

We expect that you will be in this research study for two months. The total estimated time commitment is 100 minutes. This includes a 15-minute survey upon enrollment in the study and another 15-minute survey in two months, at the end of the study. In addition, you'll be asked to complete 3-minute surveys on your phone three times/week for two months, amounting to 72 minutes spread over eight weeks.

What will I need to do to participate?

The study involves responding to survey questions and setting up a mobile texting application (15-minutes). You will then be asked to keep exercising with your Fitbit as you normally would for the next two months. On three randomly selected evenings each week, you will receive a text message at 7:00 PM with a link to complete a 3-minutes survey. Throughout this time the research team will have access to your physical activity data on your Fitbit account. At the end of two months, a final 15-minutes survey will be emailed to you. After completing this survey, you will be instructed on how to end participation, and you will receive compensation via email. Is there any way that being in this study could be bad for me? There are no known risks associated with participating in this study. As a part of this study you will be asked to exercise as you normally would. You may discontinue your participation in this study at any time without penalty. Please send us an email if you decide to discontinue participation.

Will being in this study help me in any way?

We cannot promise any benefits to you or others from your taking part in this research. However, possible benefits include improved wellness that can come from regularly exercising. Also, we will ask you to reflect on your exercise habits, and thus you may learn about routines or thought partners that help you exercise more.

What happens if I do not want to be in this research?

There are no known alternatives, other than deciding not to participate in this research study.

What happens to the information collected for the research?

Efforts will be made to limit the use and disclosure of your personal information, including research study and medical records, to people who have a need to review this information. We cannot promise complete confidentiality. Organizations that may inspect and copy your information include the Institutional Review Board (IRB), the committee that provides ethical and regulatory oversight of research, and other representatives of this institution, including those that have responsibilities for monitoring or ensuring compliance. We will not ask you about child [or vulnerable adult] abuse, but if you tell us about child [or vulnerable adult] abuse or neglect, we may be required or permitted by law or policy to report to authorities.

Secure Storage of Data Collected

Your data from participating in this research will be stored securely by the University of Minnesota, which may include electronic storage with a University-approved third-party provider. Your research records will be labeled with a code number, your date(s) of participation in the research, name, and email address. A security breach (break in or cyber-attack) might lead to someone being able to link you to your data. This risk is very low because your data are stored securely, and the information about your identity is stored separately from the other information which can be linked only through a code.

Data Sharing

In keeping with best practices in science, we plan to make selected parts of this study's dataset publicly available when the study is complete. The dataset will be stored in a scientific data repository for an indefinite period of time. These data will primarily be accessed by other scientists, and even then, that will be rare. Nevertheless, it will be possible for anyone to download the dataset from this study. The dataset we release to the public or other investigators will, to the best of our knowledge, not contain information that can directly or easily identify you. We will remove or change information that could directly or easily identify you before files are shared. The dataset we release to the public or other investigators can be used for other, future research projects without your additional consent. Those future projects can focus on any topic that might be unrelated to the goals of this study. Once the dataset has been posted to a repository it cannot be withdrawn or recalled.

Whom do I contact if I have questions, concerns or feedback about my experience?

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Checking "yes" below documents your permission to take part in this research.

- ☐ Yes, I consent to participating in the study, and I am at least 18 years old. (1)
- ☐ No, I don't consent or I don't want to participate (0)

Skip To: End of Survey If t0c.consent = 0

Page _____

Break

t0c.welcome Welcome to the study!

It is important that you answer the following questions accurately and honestly.

Your responses will be used again later in the study.

Let's get started.

Page _____

Break

t0c.demo.race Choose the race/ethnicity that you consider yourself to be:

- ☐ White (1)
- ☐ Black or African American (2)
- ☐ American Indian or Alaska Native (3)
- ☐ Asian (4)
- ☐ Native Hawaiian or Pacific Islander (5)
- ☐ Spanish, Hispanic, or Latino (6)
- ☐ Multiracial (7) _____
- ☐ Other (8) _____
-

t0c.demo.gender What is your gender?

- ☐ Male (1)
- ☐ Female (2)
- ☐ Trans (3)
- ☐ Other (4) _____
-

t0c.demo.employ Which statement best describes your current employment status?

- ☐ Working (1)
- ☐ Not Working (2) _____
- ☐ Other (3) _____

t0c.demo.student Which statement best describes your current student status?

- ☐ Full-time student (1)
- ☐ Part-time student (2)
- ☐ Not a student (3)

t0c.demo.height What is your height?

| | |
|-------------------------------|---------------------|
| Feet (t0c.demo.height_feet) | ▼ 0 (1) ... 11 (12) |
| Inches (t0c.demo.height_inch) | ▼ 0 (1) ... 11 (12) |

t0c.demo.weight What is your weight in pounds?

t0c.demo.state In which state do you currently reside?

▼ Alabama (1) ... I do not reside in the United States (53)

Page

Break

t0c.intro1

Please answer the following questions with regards to **cardiovascular exercise**.

Cardiovascular exercise is a physical activity that noticeably **increases your heart rate for at least 10 minutes**.

We are interested in cardiovascular exercise that is done during your **leisure time for recreation, or a workout**, not work-related physical activity or scheduled organized sports. You can get cardiovascular exercise in many ways, **for example, running, biking, lifting weights, or very brisk walking**.

t0c.exercises.time Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

t0c.exercises Which of the following **cardiovascular exercises** do you do on a **regular basis**? You may select more than one.

- ☐ Commute by bike (1)
- ☐ Commute by run (2)
- ☐ Commute by other (3)
- ☐ Do calisthenics (4)
- ☐ Riding a bicycle (5)
- ☐ Run/Jog (6)
- ☐ Lift weights (7)
- ☐ Swim (8)
- ☐ Walk for exercise (9)
- ☐ Yoga (10)
- ☐ Basketball (11)
- ☐ Bowling (12)
- ☐ Football (13)
- ☐ Golf (14)
- ☐ Group fitness classes (ex: indoor cycling, yoga) (15)

- ☐ Soccer (16)
- ☐ Softball/Baseball (17)
- ☐ Tennis (18)
- ☐ Volleyball (19)
- ☐ Rock climbing (20)
- ☐ Circuit training (21)
- ☐ Exercise machine (ex: elliptical stairmaster) (22)
- ☐ other: (23) _____
- ☐ other: (24) _____
- ☐ other: (25) _____

Carry Forward Selected Choices - Entered Text from "t0c.exercises"

t0c.exercises.fit Do you **usually** wear your Fitbit during the selected activities?

| | Yes (1) | No (0) |
|--------------------------------------------|-----------------------|-----------------------|
| Commute by bike (t0c.exercises.fit_x1) | <input type="radio"/> | <input type="radio"/> |
| Commute by run (t0c.exercises.fit_x2) | <input type="radio"/> | <input type="radio"/> |
| Commute by other (t0c.exercises.fit_x3) | <input type="radio"/> | <input type="radio"/> |
| Do calisthenics (t0c.exercises.fit_x4) | <input type="radio"/> | <input type="radio"/> |
| Riding a bicycle (t0c.exercises.fit_x5) | <input type="radio"/> | <input type="radio"/> |
| Run/Jog (t0c.exercises.fit_x6) | <input type="radio"/> | <input type="radio"/> |

| | | |
|--------------------------------------------------------------------------------|-----------------------|-----------------------|
| Lift weights (t0c.exercises.fit_x7) | <input type="radio"/> | <input type="radio"/> |
| Swim (t0c.exercises.fit_x8) | <input type="radio"/> | <input type="radio"/> |
| Walk for exercise (t0c.exercises.fit_x9) | <input type="radio"/> | <input type="radio"/> |
| Yoga (t0c.exercises.fit_x10) | <input type="radio"/> | <input type="radio"/> |
| Basketball (t0c.exercises.fit_x11) | <input type="radio"/> | <input type="radio"/> |
| Bowling (t0c.exercises.fit_x12) | <input type="radio"/> | <input type="radio"/> |
| Football (t0c.exercises.fit_x13) | <input type="radio"/> | <input type="radio"/> |
| Golf (t0c.exercises.fit_x14) | <input type="radio"/> | <input type="radio"/> |
| Group fitness classes (ex: indoor cycling, yoga) (t0c.exercises.fit_x15) | <input type="radio"/> | <input type="radio"/> |
| Soccer (t0c.exercises.fit_x16) | <input type="radio"/> | <input type="radio"/> |
| Softball/Baseball (t0c.exercises.fit_x17) | <input type="radio"/> | <input type="radio"/> |
| Tennis (t0c.exercises.fit_x18) | <input type="radio"/> | <input type="radio"/> |
| Volleyball (t0c.exercises.fit_x19) | <input type="radio"/> | <input type="radio"/> |
| Rock climbing (t0c.exercises.fit_x20) | <input type="radio"/> | <input type="radio"/> |
| Circuit training (t0c.exercises.fit_x21) | <input type="radio"/> | <input type="radio"/> |
| Exercise machine (ex: elliptical stairmaster) (t0c.exercises.fit_x22) | <input type="radio"/> | <input type="radio"/> |

other:
(t0c.exercises.fit_x23)

☐
☐

other:
(t0c.exercises.fit_x24)

☐
☐

other:
(t0c.exercises.fit_x25)

☐
☐

Page _____
Break

t0c.motive.intr

Previously you indicated that:

- You recently attempted to increase exercise--more active minutes or active days per week.
- After checking your Fitbit data, it was clear that you were successfully able to make this change.

When answering the following questions, **think about your personal experience during a bout of exercise since you made this change.** Focus on how you feel **in-the-moment** of exercising.

t0c.motive.intr.time Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

Page _____
Break

t0c.affect When I am exercising...

| | Strong ly agree (4) | Somew hat agree (3) | Somew hat disagree (2) | Strong ly disagree (1) |
|--------------------------------------------------------|------------------------|------------------------|---------------------------|---------------------------|
| I like the excitement of it (t0c.affect_excitement) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I enjoy it (t0c.affect_enjoyable) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| it's interesting (t0c.affect_interesting) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| it's stimulating (t0c.affect_stimulating) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Page _____
Break

t0c.satg In general, how satisfied are you with what you have experienced as a result of increasing your exercise?

- ☐ Extremely satisfied (4)
- ☐ Somewhat satisfied (3)
- ☐ Somewhat dissatisfied (2)
- ☐ Extremely dissatisfied (1)

Page _____
Break

People exercise for a variety of reasons or to meet various goals.
Select the 3 most important reasons or goals for you.
Note: you can enter your own reasons at the bottom.

- ☐ lose weight (1)
- ☐ maintain weight (2)
- ☐ improve strength (3)
- ☐ improve endurance-stamina (4)
- ☐ improve flexibility-coordination (5)
- ☐ cope with sadness-depression (6)
- ☐ cope with stress-anxiety (7)
- ☐ increase energy level (8)
- ☐ improve mood (9)
- ☐ improve overall health (10)
- ☐ improve appearance (11)
- ☐ meet new people (12)
- ☐ have fun (13)
- ☐ improve overall body shape (14)
- ☐ other (15) _____
- ☐ other (16) _____
- ☐ other (17) _____

Carry Forward Selected Choices - Entered Text from "t0c.sats.top"

t0c.sats How satisfied are you that your **current level of exercise** is achieving your goals or reasons for exercising?

| | Extreme ly satisfied (4) | Somewh at satisfied (3) | Somewh at dissatisfied (2) | Extreme ly dissatisfied (1) |
|-----------------------------------------------------------|-----------------------------|----------------------------|-------------------------------|-----------------------------------|
| lose weight (t0c.sats_x1) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| maintai n weight (t0c.sats_x2) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| improv e strength (t0c.sats_x3) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| improv e endurance- stamina (t0c.sats_x4) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| improv e flexibility- coordination (t0c.sats_x5) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| cope with sadness- depression (t0c.sats_x6) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| cope with stress- anxiety (t0c.sats_x7) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| increas e energy level (t0c.sats_x8) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| improv e mood (t0c.sats_x9) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| improv e overall health (t0c.sats_x10) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

| | | | | |
|----------------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| improve appearance (t0c.sats_x11) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| meet new people (t0c.sats_x12) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| have fun (t0c.sats_x13) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| improve overall body shape (t0c.sats_x14) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| other (t0c.sats_x15) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| other (t0c.sats_x16) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| other (t0c.sats_x17) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Page _____

Break

t0c.prep.intr

Cardiovascular exercise (such as running, biking, or lifting weights) often requires some **preparation**.

Examples:

- Packing a gym bag the night before going to the gym.
- Planning to go to the gym at the beginning of a lunch break or upon arriving home from work/school.
- Deciding whether to exercise or do something else such as spend time with a friend or make dinner.

t0c.prep.intr.time Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

t0c.inst.select What type of **preparation** do you typically do before exercising?
Select all that apply.

- ☐ scheduling (1)
- ☐ readying supplies, clothes, or equipment (2)
- ☐ traveling to an exercise location (3)
- ☐ thinking about whether I'd rather do something else (4)
- ☐ thinking about the best time (or how to make time) for exercise (5)
- ☐ contacting others with whom I exercise (6)
- ☐ taking care of other responsibilities (ex: ensuring someone can watch the kids) (7)
- ☐ other: (8) _____
- ☐ other: (9) _____
- ☐ other: (10) _____

Page _____

Break

t0c.prep.intr2 We are interested in differences between **preparing** to exercise and **engaging in the act** of exercise.

Respond to each of the following questions for:

- (A) **preparing** to exercise.
- (B) **engaging in the act** of exercise.

t0c.prep.intr2.time Timing
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

Page _____

Break

t0c.srbai.inst (A) **Preparing** to exercise is something...

| | Stron gly agree (4) | Somew hat agree (3) | Somew hat disagree (2) | Stron gly disagree (1) |
|--------------------------------------------------------------------------------------|------------------------|------------------------|---------------------------|------------------------------|
| I do without having to consciously remember. (t0c.srbai.inst_remem ber) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I do without thinking. (t0c.srbai.inst_thinkin g) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I start doing before I realize I'm doing it. (t0c.srbai.inst_realizin g) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Page _____

Break

t0c.srbai.per (B) **Engaging in the act** of exercise is something...

| | Stron gly agree (4) | Somew hat agree (3) | Somew hat disagree (2) | Stron gly disagree (1) |
|-------------------------------------------------------------------------------------|------------------------|------------------------|---------------------------|------------------------------|
| I do without having to consciously remember. (t0c.srbai.per_remem ber) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I do without thinking. (t0c.srbai.per_thinkin g) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I start doing before I realize I'm doing it. (t0c.srbai.per_realizin g) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

t0c.woodg.inst When I **prepare** to exercise, I typically do it in a similar way each time.

- ☐ Strongly agree (4)
- ☐ Somewhat agree (3)
- ☐ Somewhat disagree (2)
- ☐ Strongly disagree (1)
-

Page _____

Break

t0c.woodg.per When I **engage in the act** of exercise, I typically do it in a similar way each time.

- ☐ Strongly agree (4)
- ☐ Somewhat agree (3)
- ☐ Somewhat disagree (2)
- ☐ Strongly disagree (1)
-

Page _____

Break

t0c.woods.inst In general, each time I **prepare** to exercise...

| | Exactly the same as usual (4) | Very similar to usual (3) | Somewhat similar to usual (2) | Not at all similar to usual (1) |
|-----------------------------------------------------------------------|-------------------------------------|---------------------------------|-------------------------------------|---------------------------------------|
| the LOCATION in which I do it is... (t0c.woods.inst_loc) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| the TIME OF DAY at which I do it is... (t0c.woods.inst_time) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| my MOOD is... (t0c.woods.inst_mood) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Page _____

Break

t0c.woods.per In general, each time I **engage in the act of exercise...**

| | Exactly the same as usual (4) | Very similar to usual (3) | Somewhat similar to usual (2) | Not at all similar to usual (1) |
|----------------------------------------------------------------------|-------------------------------------|---------------------------------|-------------------------------------|---------------------------------------|
| the LOCATION in which I do it is... (t0c.woods.per_loc) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| the TIME OF DAY at which I do it is... (t0c.woods.per_time) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| my MOOD is... (t0c.woods.per_mood) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| the PEOPLE with whom I do it are... (t0c.woods.per_people) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

End of Block: Default Question Block

Start of Block: register survey signal

t0c.instruct

Thank you, \${e://Field/RecipientFirstName}!

You are now ready to register for the mobile phase of the study.

Important Instructions for Mobile Phase of Study

Over **the next two months**, we'd like you to **continue exercising with your Fitbit as you normally would**.

During this time, we will send you a 3-minute survey at 7:00 PM on three randomly selected evenings each week. Please respond to surveys the day you receive them (each link will expire at midnight). At 8 PM you will get a reminder text if you haven't already completed that day's survey.

Please remember to charge and sync your Fitbit to your account **at least** once per week.

When you go to the next page, you will be redirected to **SurveySignal Registration Page**. We will set up your phone with our system and verify that it works.

At the end of two months, we will send you a final survey via email, after which you will receive compensation also via email.

These instructions will be emailed.

Please continue when you are ready.

☐ Yes, I read these important instructions. I'm ready to register my phone. (1)

t0c.instruct.time Timing

First Click (1)

Last Click (2)

Page Submit (3)

Click Count (4)

End of Block: register survey signal

Observation Period Survey (Figure 7, T1)

Survey Flow

| |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <p>EmbeddedData PIDValue will be set from Panel or URL.</p> |
| <p>Authenticator: Single Sign On - Token</p> |
| <p>EmbeddedData SSIDValue will be set from Panel or URL. PIDValue will be set from Panel or URL. RIDValue will be set from Panel or URL. SMSValue will be set from Panel or URL. DAYValue will be set from Panel or URL. SIGValue will be set from Panel or URL. RDateValue will be set from Panel or URL. TIMEValue will be set from Panel or URL. RTValue will be set from Panel or URL. TimeZoneValue will be set from Panel or URL. DateTakenValue will be set from Panel or URL. TriggerResponseIDValue will be set from Panel or URL. TriggerSurveyIDValue will be set from Panel or URL. ExercisesValue will be set from Panel or URL. rdayValue will be set from Panel or URL. rsigValue will be set from Panel or URL. Exercise ReasonsValue will be set from Panel or URL.</p> <p>EmbeddedData reason1Value will be set from Panel or URL. reason2Value will be set from Panel or URL. reason3Value will be set from Panel or URL.</p> <p>EmbeddedData QCity_ExportTagValue will be set from Panel or URL. QState_ExportTagValue will be set from Panel or URL.</p> |
| <p>Block: intro (2 Questions) Standard: exercise (14 Questions) Standard: prep (7 Questions)</p> |
| <p>EndSurvey:</p> |

Page

Break

Start of Block: intro

t1.meta Browser Meta Info

Browser (1)

Version (2)

Operating System (3)

Screen Resolution (4)

Flash Version (5)

Java Support (6)

User Agent (7)

Q35

Hello \${e://Field/RecipientFirstName}! You're on day \${e://Field/DAY} of 56 in the study.

Page _____
Break

End of Block: intro

Start of Block: exercise

JS

t1.exercisetoday Did you complete 10+ minutes of cardiovascular exercise **today**?
Examples: workouts that noticeably increase your heart rate such as running, biking, or lifting weights.

☐ Yes (1)

☐ No (0)

Skip To: t1.whynoexercise If t1.exercisetoday = 0

Page _____
Break

| t1.srbai.per.today | Today's exercise was something... | | | |
|-----------------------------------------------------------------------------------|------------------------------------------|-----------------------|-----------------------|-----------------------|
| | Strongly agree (4) | Somewhat agree (3) | Somewhat disagree (2) | Strongly disagree (1) |
| I did without having to consciously remember (t1.srbai.per.today_remember) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I did without thinking (t1.srbai.per.today_thinking) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I started doing before realizing I was doing it (t1.srbai.per.today_realizing) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Page _____

Break

| t1.woods.per.today | For today's exercise ... | | | |
|-----------------------------------------------------------------------|---------------------------------|---------------------------|-------------------------------|---------------------------------|
| | Exactly the same as usual (4) | Very similar to usual (3) | Somewhat similar to usual (2) | Not at all similar to usual (1) |
| the LOCATION in which I did it was... (t1.woods.per.today_loc) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| the TIME OF DAY at which I did it was... (t1.woods.per.today_time) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| my MOOD was... (t1.woods.per.today_mood) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| the PEOPLE with whom I did it were... (t1.woods.per.today_people) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Page
Break

t1.exercisegroup **Today**, did you **exercise** with other people (or as part of a group)?

☐ Yes (1)

☐ No (0)

Display This Question:

If t1.exercisegroup = 1

t1.exercisegroup.num How many others?

☐ 1 (1)

☐ 2 (2)

☐ 3 (3)

☐ 4 or more (4)

Page _____

Break

t1.affect.today Reflect on the **exercise** you did **today**. To what extent do the following describe your experience during **today's exercise**?

| | Strongly agree (4) | Somewhat agree (3) | Somewhat disagree (2) | Strongly disagree (1) |
|------------------------------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| There was excitement in it (t1.affect.today_excitement) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| It was enjoyable (t1.affect.today_enjoyable) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| It was interesting (t1.affect.today_interesting) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| It was stimulating (t1.affect.today_stimulating) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Page _____

Break

t1.satg.today How satisfied are you with **what you have experienced** as a result of **exercising today**?

- ☐ Extremely satisfied (4)
- ☐ Somewhat satisfied (3)
- ☐ Somewhat dissatisfied (2)
- ☐ Extremely dissatisfied (1)

Page _____

Break

t1.sats.today How satisfied are you that **your current level of exercise** is achieving your goals or reasons for exercising?

| | Extre mely satisfied (4) | Some what satisfied (3) | Some what dissatisfied (2) | Extre mely dissatisfied (1) |
|---------------------------------------------------------|--------------------------------|-------------------------------|----------------------------------|-----------------------------------|
| <code>{e://Field/rea son1}</code> (t1.sats.today_1) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| <code>{e://Field/rea son2}</code> (t1.sats.today_2) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| <code>{e://Field/rea son3}</code> (t1.sats.today_3) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Display This Question:

If t1.exercisetoday = 0

t1.whynoexercise Why not? Select all that apply.

- ☐ Too busy (1)
 - ☐ Too tired (2)
 - ☐ Too stressed (3)
 - ☐ I forgot (4)
 - ☐ It's unpleasant (5)
 - ☐ It was a planned day off (6)
 - ☐ Other (7) _____
-

Page _____

Break

Display This Question:
If t1.exercisetoday = 0



t1.srbai.per.recent Recently, when I have **exercised**, it's something...

| | Stron gly agree (4) | Some what agree (3) | Some what disagree (2) | Stron gly disagree (1) |
|----------------------------------------------------------------------------------------------|------------------------|------------------------|------------------------------|------------------------------|
| I did without having to consciously remember (t1.srbai.per.recent_reme mber) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I did without thinking (t1.srbai.per.recent_think ing) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I started doing before realizing I was doing it (t1.srbai.per.recent_realiz ing) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Display This Question:
If t1.exercisetoday = 0

| t1.woods.per.recent | Recently, when I have exercised... | | | |
|------------------------------------------------------------------------------|--------------------------------------|----------------------------------|--------------------------------------|-------------------------------------------|
| | Exactl y the same as usual (4) | Ver y similar to usual (3) | Somewh at similar to usual (2) | No t at all similar to usual (1) |
| the LOCATION in which I did it was... (t1.woods.per.recent_loc) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| the TIME OF DAY at which I did it was... (t1.woods.per.recent_time) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| my MOOD was... (t1.woods.per.recent_mood) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| the PEOPLE with whom I did it were... (t1.woods.per.recent_peopl e) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Display This Question:
If t1.exercisetoday = 0



t1.affect.recent Reflect on the **exercise** you **did in the recent past**. To what extent do the following describe **your experience during** that exercise.

| | Strongly agree (4) | Somewhat agree (3) | Somewhat disagree (2) | Strongly disagree (1) |
|-------------------------------------------------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| There was excitement in it (t1.affect.recent_excitement) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| It was enjoyable (t1.affect.recent_enjoyable) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| It was interesting (t1.affect.recent_interesting) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| It was stimulating (t1.affect.recent_stimulating) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Page _____
Break

Display This Question:

If t1.exercisetoday = 0

t1.satg.recent Reflect on the **exercise** you **did in the recent past**. How satisfied are you with **what you have experienced** as a result of exercising?

- ☐ Extremely satisfied (4)
- ☐ Somewhat satisfied (3)
- ☐ Somewhat dissatisfied (2)
- ☐ Extremely dissatisfied (1)

Page _____
Break

Display This Question:
If *t1.exercisetoday* = 0

t1.sats.recent How satisfied are you that **your current level of exercise** is achieving your goals or reasons for exercising?

| | Extre mely satisfied (4) | Some what satisfied (3) | Some what dissatisfied (2) | Extre mely dissatisfied (1) |
|-----------------------------------------------------------|--------------------------------|-------------------------------|----------------------------------|-----------------------------------|
| <i>{e://Field/reason1}</i> (<i>t1.sats.recent_1</i>) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| <i>{e://Field/reason2}</i> (<i>t1.sats.recent_2</i>) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| <i>{e://Field/reason3}</i> (<i>t1.sats.recent_3</i>) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

End of Block: exercise

Start of Block: prep

Display This Question:
If *t1.exercisetoday* = 0

t1.preptoday.0 Even though you didn't exercise today, did you plan/**prepare** to exercise today?

Examples: clearing time in your schedule, getting clothes ready, organizing with a friend, making an appointment, deciding whether it's worth the time/effort, etcetera.

☐ Yes (1)

☐ No (0)

Skip To: *t1.whynoprep* If *t1.preptoday.0* = 0

Display This Question:

If $t1.exercisetoday = 1$

$t1.preptoday.1$ Did you **prepare** for today's exercise?

Examples: clearing time in your schedule, getting clothes ready, organizing with a friend, making an appointment, deciding whether it's worth the time/effort, etcetera.

☐ Yes (1)

☐ No (0)

Skip To: $t1.whynoprep$ If $t1.preptoday.1 = 0$

Page _____

Break

$t1.srbai.inst.today$ **Preparing** to exercise **today**, was something...

| | Strongly agree (4) | Some what agree (3) | Some what disagree (2) | Strongly disagree (1) |
|-----------------------------------------------------------------------------------------|-----------------------|-----------------------|------------------------|-----------------------|
| I did without having to consciously remember ($t1.srbai.inst.today_remember$) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I did without thinking ($t1.srbai.inst.today_thinking$) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I started doing before realizing I was doing it ($t1.srbai.inst.today_realizing$) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Page _____

Break

$t1.woods.inst.today$ When I **prepared** for **today's** exercise...

| | Exactly the same as usual (4) | Very similar to usual (3) | Somewhat similar to usual (2) | Not at all similar to usual (1) |
|--|-------------------------------|---------------------------|-------------------------------|---------------------------------|
| | | | | |

the LOCATION in
which I did it was...
(t1.woods.inst.today_loc)

☐☐☐☐

the TIME OF
DAY at which I did it
was...
(t1.woods.inst.today_time)

☐☐☐☐

my MOOD was...
(t1.woods.inst.today_mood)

☐☐☐☐

Display This Question:

If $t1.preptoday.1 = 0$

t1.whynoprep Why not? Select all that apply.

☐

Too busy (1)

☐

Too tired (2)

☐

Too stressed (3)

☐

I forgot (4)

☐

It's unpleasant (5)

☐

It was a planned day off (6)

☐

Exercise I did today was impromptu (unplanned) (7)

☐

Other (8) _____

Page _____

Break

Display This Question:
If $t1.preptoday.1 = 0$

t1.srbai.inst.recent Recently, when I have **prepared** to exercise, it was something...

| | Stron gly agree (4) | Some what agree (3) | Some what disagree (2) | Stron gly disagree (1) |
|-----------------------------------------------------------------------------------------------|------------------------|------------------------|------------------------------|------------------------------|
| I did without having to consciously remember (t1.srbai.inst.recent_reme mber) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I did without thinking (t1.srbai.inst.recent_think ing) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| I started doing before realizing I was doing it (t1.srbai.inst.recent_realiz ing) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

Display This Question:
If $t1.preptoday.1 = 0$

| | | | | |
|-------------------------------------------------------------------------------|------------------------------------------------------|----------------------------------|--------------------------------------|-------------------------------------------|
| t1.woods.inst.recent | Recently, when I have prepared to exercise... | | | |
| | Exactl y the same as usual (4) | Ver y similar to usual (3) | Somewha t similar to usual (2) | No t at all similar to usual (1) |
| the LOCATION in which I did it was... (t1.woods.inst.recent_loc) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| the TIME OF DAY at which I did it was... (t1.woods.inst.recent_time) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |
| my MOOD was... (t1.woods.inst.recent_moo d) | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> |

End of Block: prep

Follow-up Survey (Figure 7, T02)

Survey Flow

Authenticator: Single Sign On - Token

EmbeddedData

DateTakenValue will be set from Panel or URL.

TriggerResponseIDValue will be set from Panel or URL.

TriggerSurveyIDValue will be set from Panel or URL.

ExercisesValue will be set from Panel or URL.

counterValue will be set from Panel or URL.

rdayValue will be set from Panel or URL.

rsigValue will be set from Panel or URL.

Exercise ReasonsValue will be set from Panel or URL.

Fitbit emailValue will be set from Panel or URL.

PIDValue will be set from Panel or URL.

RIDValue will be set from Panel or URL.

SSIDValue will be set from Panel or URL.

SS RegistrationValue will be set from Panel or URL.

Block: Default Question Block (17 Questions)

EndSurvey: Advanced

Page _____

Break

Start of Block: Default Question Block

t2.meta Browser Meta Info

Browser (1)

Version (2)

Operating System (3)

Screen Resolution (4)

Flash Version (5)

Java Support (6)

User Agent (7)

t2.welcome

Hi \${e://Field/RecipientFirstName}!

This is the final survey you will be asked to take as a part of this study.

Page _____

Break

T2.palevel During the study, my level of physical exercise was [-- FILL IN THE BLANK--] than it was before I started the study two months ago.

- ☐ much lower (-2)
- ☐ slightly lower (-1)
- ☐ no different (0)
- ☐ slightly higher (1)
- ☐ much higher (2)

Page _____
Break

Display This Question:

If T2.palevel = 1

Or T2.palevel = 2

t2.pawhyinc In 1-2 sentences, please explain why you think you were able to increase your level of exercise during the study.

Display This Question:

If T2.palevel = 0

t2.pawhymain In 1-2 sentences, please explain why you think you were able to maintain your level of exercise during the study.

Display This Question:

If T2.palevel = -2

Or T2.palevel = -1

t2.pawhydec In 1-2 sentences, please explain why you think you weren't able to maintain a high level of exercise during the study.

Page _____

Break

t2.pafuture Over the next 3 months, do you think you will be able to keep exercising as much as you did during the study?

- ☐ Extremely likely (4)
- ☐ Somewhat likely (3)
- ☐ Somewhat unlikely (2)
- ☐ Extremely unlikely (1)

Page _____

Break

Q64

Please respond to each of the following honestly.

Your response **will not affect** your compensation or standing in the study.

t2.vaca Did you go on vacation, travel out of state, or move during your participation this study?

- ☐ Yes (1)
- ☐ No (0)

Display This Question:

If $t2.vaca = 1$

t2.vaca.pa Did it affect your ability to exercise?

- ☐ Made it harder (1)
 - ☐ Made is easier (2)
 - ☐ It didn't affect my ability exercise (3)
 - ☐ Other (4) _____
-

t2.sick Were you ever sick, ill, or injured in a way that affected your ability to exercise during the study?

- ☐ Yes (1)
 - ☐ No (0)
-

t2.techissue Did you have any technical issues during the study that affected your ability to complete surveys or sync your Fitbit to your account?

- ☐ Yes (1)
- ☐ No (0)

t2.fitwear During the study, how often were you wearing your Fitbit?

- ☐ Every day (5)
 - ☐ Nearly every day (4)
 - ☐ Very often (3)
 - ☐ Often (2)
 - ☐ Rarely (1)
 - ☐ Never (0)
-

t2.fitsync How often did you sync your Fitbit to your account?

- ☐ Every day (4)
 - ☐ Every other day (3)
 - ☐ Every week (2)
 - ☐ Every month (1)
 - ☐ Never (0)
-

t2.issues Any other issues during the study? Select all that apply.

- ☐ Fitbit lost, stolen, or broken (1)
 - ☐ Didn't get text messages (2)
 - ☐ Link in text message wouldn't open (3)
 - ☐ Other (4) _____
 - ☐ No other issues (5)
-

t2.openshare Anything else you'd like to share about your experience in the study?

Page _____
Break

Q74

Thank you, \${m://FirstName}! The study is over!

IMPORTANT INFORMATION

- Please **change your Fitbit Password, again!**
- We will no longer access your account.
- You will receive an email within 5 business days that contains **compensation** for participating in this study.

Questions? Email: fitstudy@umn.edu

How to change Fitbit password:

End of Block: Default Question Block
Appendix B: Classifying successful and unsuccessful maintenance

Appendix B: Classification of successful and unsuccessful maintenance

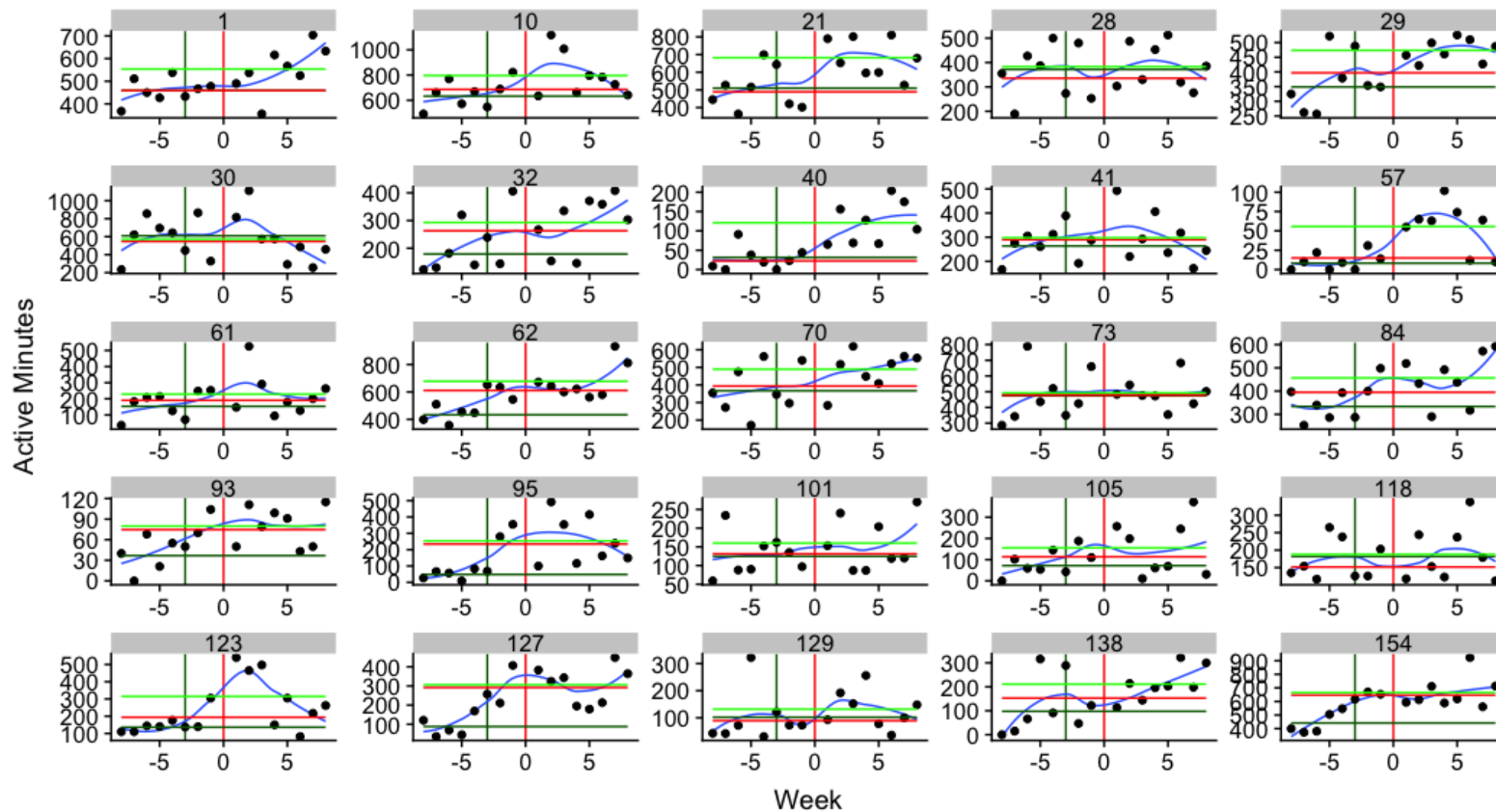


Figure B1. Participants who were classified as successful maintainers (n=25).

Note: For each participant, every observation of weekly activity is plotted (black points) and a local polynomial regression (LOESS) was fit (blue line). Vertical lines mark the end of a period: Participants initiated an increase in activity Weeks -8 through -6 (dark green), and they qualified for the study by maintain that higher level of activity in Weeks -5 through -1 (red). Horizontal lines represent the mean during a period: initiation (dark green), qualification (red), and observation (light green). Participants were classified as successful maintainers when their mean activity level during observation (light green) was larger than that during qualification (red).

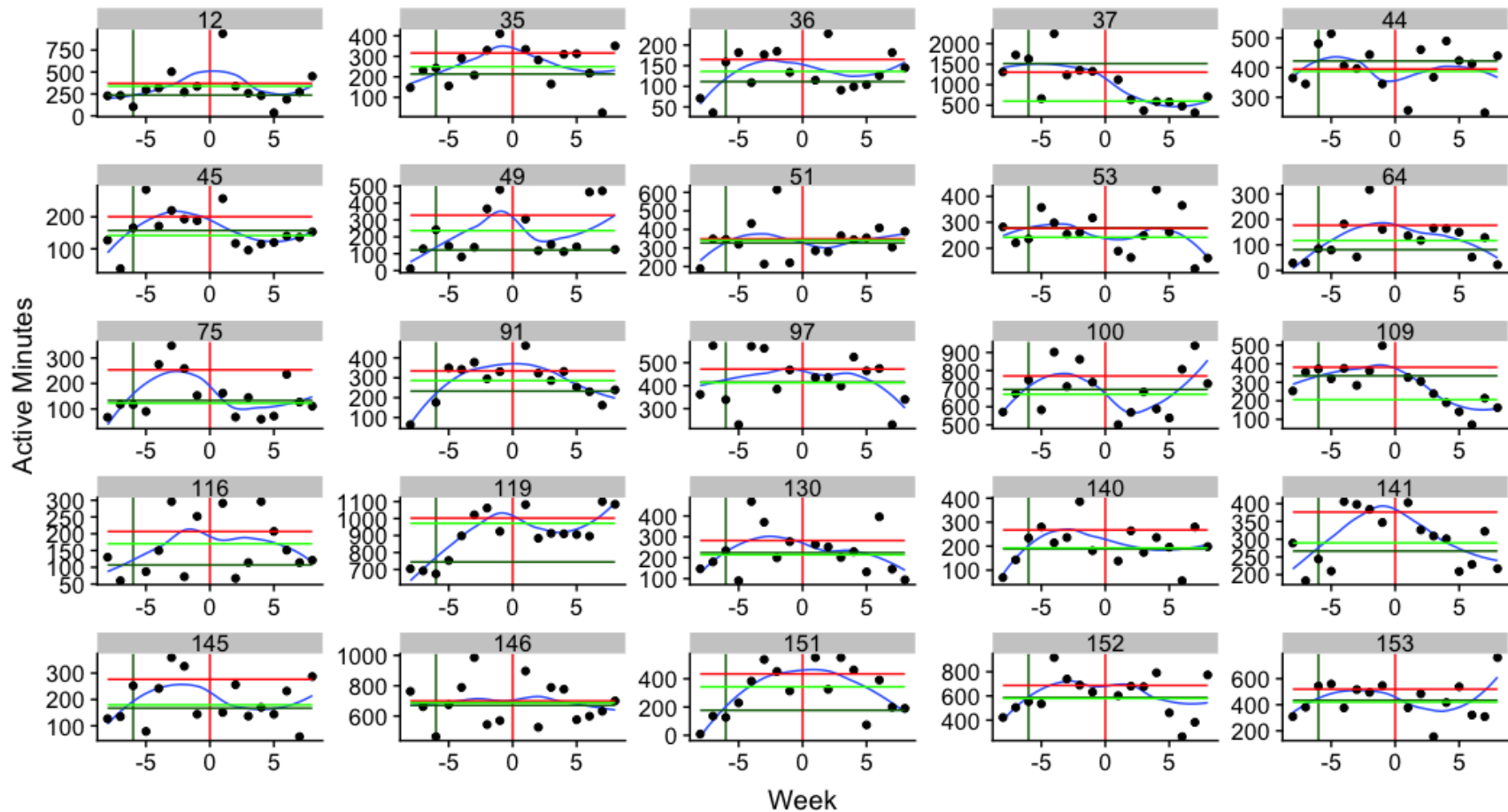


Figure B2. Participants who were classified as unsuccessful maintainers (n=25).

Note: For each participant, every observation of weekly activity is plotted (black points) and a local polynomial regression (LOESS) was fit (blue line). Vertical lines mark the end of a period: Participants initiated an increase in activity Weeks -8 through -6 (dark green), and they qualified for the study by maintain that higher level of activity in Weeks -5 through -1 (red). Horizontal lines represent the mean during a period: initiation (dark green), qualification (red), and observation (light green). Participants were classified as unsuccessful maintainers when their mean activity level during observation (light green) was less or equal to than that during qualification (red).